2017

Extending External Agent Capabilities in Healthcare Social Networks

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by

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A Thesis
Submitted to the Faculty of Graduate Studies
through the School of Computer Science
in Partial Fulfillment of the Requirements for
the **Degree of Master of Science**
at the University of Windsor

Windsor, Ontario, Canada
2017

Extending External Agent Capabilities in Healthcare Social Networks

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Declaration of Co-Authorship/Previous Publication

1- Co-Authorship Declaration

I hereby declare that this dissertation incorporates material that is the result of research conducted under the supervision of Dr. Ziad Kobti (my supervisor). In all cases, the key ideas, primary contributions, experimental designs, data analysis and interpretation, were performed by the author, and the contribution of co-authors was primarily through the proofreading of the published manuscripts. Dr. Pooya Moradia Zadeh and Dr. Kathryn Pfaff also contributed in collecting data and explaining the materials.

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Section	Full Citation	Publication Status
All chapters	Moradianzadeh, N., Zadeh, P. M., Kobti, Z. & Pfaff. K. (2017). An Agent Model to Support-based Palliative Care. In 2017 IEEE Symposium on Computers and Communication (ISCC)-(2nd ICTS4EHealth workshop) . IEEE, 2017.	In press

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Abstract

A social health care system, such as palliative care, can be viewed as a social network of interacting patients and care providers. Each patient in the network has a set of capabilities to perform his or her intended daily tasks. However, some patients may not have the required capabilities to carry out their desired tasks. Consequently, different groups of care providers - consist of doctors, volunteers, nurses, etc.- offer the patients support by providing them with a variety of needed services.

Assuming there are a cost and resource limitations for providing care within the system, where each care provider can support a limited number of patients, the problem is to find a set of suitable care providers to match the needs of the maximum number of patients.

In this dissertation, we propose a novel agent-based model to address this problem by extending the agent's capabilities using the benefit of the social network. Our assumption is that each agent, or patient, can cover its disabilities and perform its desired tasks through collaboration with other agents, or care providers, in the network.

The goal of this work is to improve the quality of services in the network at both individual and system levels. On the one hand, an individual patient wants to maximize the quality of his/her life, while at the system level we want to achieve quality care for as many patients as possible with minimum cost. The performance and functionality of this proposed model have been evaluated based on various synthetic networks.

The results demonstrate a significant reduction in the operational costs and enhancement of the service quality.

Dedication

To my loving family:

Mother: Manijeh Bouyeh

Father: Mohammad Moradian Zadeh

Brother: Pooya Moradian Zadeh

Acknowledgments

I would like to thank my parents for their counsel and the sympathetic ear. They are always there for me and support me in all possible ways. Next, I would like to thank to my brother who helped me a lot during my study with his wise counsel and his knowledge. His guidance helped me all the time.

I also would like to express my sincere to my supervisor Dr. Ziad Kobti that gave me chance to work in different projects which were an amazing experience for me. His constant motivation, continuous support and faith guided me in on my works during my study. I really appreciate for his encouragement with his innovative ideas and being wonderful mentor.

In addition, Many thanks to my committee members Dr. Kathryn Pfaff, and Dr. Mehdi Kargar for their valuable time and their supports.

I would like to express my appreciation to Ms. Gloria Mensah, Ms. Karen Bourdeau, and Ms. Margaret Garabon who always supported me when I needed assistance in various academic issues.

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Chapter 1

Introduction

The aging population has been growing rapidly in the world. Statistics show that by 2050, elderly people who have 60 years old and more will shape around 20 percent of the world population, while this rate now is approximately 10 percent of the population[3]. With aging, the risk of contracting diseases, especially chronic diseases, increases along with other health related problems. Therefore, the need of improving healthcare systems can be considered as a critical issue to enhance the quality of healthcare services. In addition, the service must be accessible to everyone with a reasonable cost.

On the other hand, the spread of the Internet, computer networks, recent developments in electronics such as sensors and wireless technologies have helped experts to propose various solutions to deal with the healthcare problems [28]. Using the Internet and networks, possible to share the experimental data and access to the benchmarks much easier and faster than before. For example, a lot of Electronic Health Record (EHR) data have been shared on-line which can be used to study some particular problems of healthcare systems. As a result, in recent years, artificial intelligence techniques are frequently used for the data analysis purpose in the field of healthcare.

One of the proposed AI approach to deal with the healthcare problems is to simulate the system using Multi-Agent models. The healthcare system is a complex structure consists of multiple actors who are interacting with each other in different ways. Making a decision in this system is a hard task which needs a complicated analytic process. Multi-agent modeling can be used to simulate various types of scenarios and help the process of decision making [16] [10]. Exploring the behavior of the system in a controlled environment is another advantage of Multi-Agent Systems (MAS) for the experts [21]. Generally, in this approach, a complex task is broken into smaller tasks, and each of them is assigned to an agent. Therefore, each agent has its own particular goals and responsibilities.

In this thesis, our goal is to develop a MAS to model the palliative care system where patients are not able to perform some of their daily tasks. Our proposed method is to map the system to a social network, where patients and care providers are its main social actors. Patients here are older adults or people who suffer chronic or terminal diseases with loss of capabilities. The primary goal of our method is to find the best person or care provider team that can collaborate with the patient to do his/her daily tasks with the minimum costs and maximum satisfaction rate. Our assumption is that the require capabilities of each patient can be covered through his/her social circles. Our proposed approach is not limited to this particular problem, but also it can be applied in any other situations when social actors do not have some of the required capabilities, and the system must be traced to find the best candidates to cover these disabilities.

In this chapter, we first review some of the related fundamental topics and then, the problem definition, our research objectives, and research contributions are discussed in details.

1.1 Background

1.1.1 Social Systems

A social system can be described as a group of interacting social actors with common goals or orientations[26]. Family groups, neighbors, circle of friends and healthcare systems are some of the examples of these systems which play key roles in human activities and life. Due to their critical impacts on the society and people, they are studied from both individual and systematic perspectives. A social system can help experts to classify the society into social systems to study the behavior and interactions among members.

Parsons in [26] mentioned that each social system imperatively needs the AGIL (Adaptation, Goal attainment, Intention, Latency) characteristics. The author also mentioned that the stability of a social system can guarantee by enhancing these features. Goal attainment concerns about goal settings and decision making in the society. Adaptation shows how much a social system can interact with the environment. Integration refers to the strengthen relations between actors and finally, Latency is about the roles, needs, and motives of the actors in the society.

1.1.2 Health care Systems- Palliative Care

The healthcare system is a social system where different types of actors play their roles in order to improve and maintain patient's physical or mental health. The health care social system consists of variety types of actors (e.g. doctors, patients, organizations, etc.) who have different goals and responsibilities. This system can be seen as a network where the nodes are various types of actors, includes care providers or patients, and edges are connections between them.

Palliative care is an example of healthcare social system which used in this thesis as a case study. Palliative care is a particular type of healthcare which focuses on improving the patient's quality of life who are living with life-threatening illness or nearing the end of life. This approach may be taken into an account if there is no chance for a cure. The primary goal here is to provide various support services to help the patients having an active and comfort life during the remaining time [33]. As shown in Fig. 1.1, a team of care providers including family members, nurses, volunteers, and doctors are involved in this process.

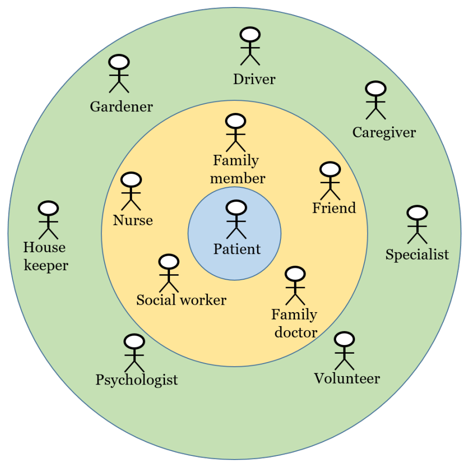


Figure 1.1: Social care circle in a palliative care system

1.1.3 Intelligent Agent

The term of "agent" has multiple definitions in different areas [10], but S.Russell and P.Norvig [30] described different types of agents in the field of Artificial Intelligence(AI). A simple agent is an agent which only receives data from the environment and react to the environment. This agent matches the received data about the current situation of the environment and the rules on the agent and chose the best action according to that. A problem-solving agent, which is a type of goal-based agents, make a decision to choose a proper action based on the environmental situations and the agent's goals. In another word, it measures the effect of its acts on the environment to find out how the series of actions can lead it to the acceptable states (goal). A learning agent is another type of agent which is able to keep and store the obtained knowledge of its previous experiences and use them in the future action selection process.

Therefore, an intelligent agent can be defined as a problem-solving entity which is working autonomously in the environment to achieve an individual goal. In another word, an intelligent agent is a goal-driven entity. In addition, an intelligent agent is adaptable to the environment and receives the data from the environment by sensors and react to the environment by actuators [17], [21], [30]. A simple agent is shown in fig 1.2.

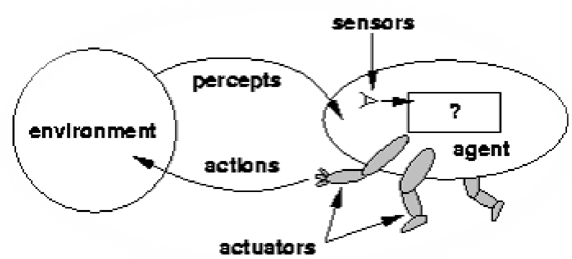


Figure 1.2: A simple agent [30]

1.1.4 Multi-Agent System(MAS)

A Multi-Agent System(MAS) is a system that consists of several intelligent agents that interact with each other to solve a common problem. In this system, each agent has a particular responsibility and role, such as a seller or a consumer. They have mutual influences on each other which lead them to achieve their goals [21]. A MAS can be beneficial where an environment has some characteristics such as heterogeneous and complex interactions, heterogeneous population size, or complex agent's behaviors(e.g. learning) [4]. Moreover, MAS is suggested for the systems that deal with a large amount of data. In MAS a task is breaking down to the subtasks and assigned to each agent. So, the system easily can be implemented and explored [21].

As mentioned before, MAS can help experts to simulate and monitor the behavior of dynamic social networks to solve a particular problem in the society in a case of the complex issue which must be broken into smaller pieces. In the recent years, this approach has been used to solve various types of problems in different fields such as marketing, anthropology, etc. MASs also have been used widely to model healthcare systems where a huge amount of data and criteria are needed for solving a problem.

In the field of healthcare systems, the applications of MAS can be categorized by different criteria [15]. Regarding MAS applications, these systems can be classified into data management, distributed system's security, decision support systems(DSS), resource planning, simulation systems, care platform, monitoring and alarming systems [15]. Furthermore, these approaches have focused on different groups of actors including patients, staffs, and organizations. In addition, a system may focus on more than one type of actors. Some of these approaches are discussed in the next chapter as the related works.

1.2 Research Motivation

In the last decade, different types of multi-agent based decision support systems have been proposed to deal with various types of problem in the healthcare systems. These support systems can be used to provide appropriate healthcare services to the patients which is the first and foremost incentive of this thesis, as a part of humanity.

Additionally, the widespread of the Internet and recent developments in the electronics and wireless technologies provide a broad range of innovative digital tools and analytic techniques for researchers to cope with the wide range of healthcare problems [28]. The number Body Area Network(BAN) developed a lot to send types of data from the patients. Also, Internet of Thing (IoT) helps the experts to send and receive the real-time data. These technologies provide access to the broad range of shared information which can be used to exploring the healthcare systems.

On the other hand, the healthcare system consists of linked social circles of the care, a set of attributes and a series of profile information. In a larger scale, the whole care system can be seen as a social network consists of patients and care providers who are linked together.

The fact is, very few research works have explored the system from the social network perspective. We believe that looking at the system as a social network and applying social network techniques on it can enhance both planning and task allocation processes. The advantages of the social network can help the system to minimize the operational costs and maximize the overall service quality.

1.3 Problem Statement

Health care system can be seen as a complex social system. One of the examples of the healthcare system is palliative care system which is used in this thesis as a case study.

As described before, the palliative care system consists of two main classes which are patients and care providers. Each patient has a set of capabilities and goals, which can be defined as $ag^p \in AG \triangleq (G_{ag^p}, C_{ag^p})$, where $C_{ag^p} = \{c_1, \ldots, c_n\}$ denotes the set of n capabilities for each patient. For example, c_1 can be the ability to walk independently, and c_2 the capability of speaking. For each patient, the set of capabilities can be split into two sets of internal and external capabilities, hence $C_{ag^p} = \{C_{IN} \cup C_{EX}\}$ and $C_{EX} \cap C_{IN} = \emptyset$. The internal capabilities are those abilities that a patient already have which can be represented by a fixed-size binary vector as $C_{IN} = [c_1, \ldots, c_n]$, where $c_i, 1 \leq i \leq n$ is 1 if a patient has the corresponding ability and it is 0 in the other case.

The external capabilities are those abilities that a patient does not have but can be obtained with the help of the care providers. Similar to the internal capability it can be represented by a fixed-size binary vector as $C_{EX} = [c_1, \ldots, c_n]$.

In addition, each patient has a set of goals which can be achieved by performing some specific tasks. Let $g \in G_{ag^p} \triangleq (gid, TS)$ shows a goal where gid is used to identify the goal and TS is a set of required tasks to achieve it. Each task is defined as $ts \in TS \triangleq (tid, RC)$ where, RC is the required capabilities to perform the task and is represented as $RC \triangleq (rc_1, \ldots, rc_m)$.

Consequently, the main problem here is that some of the patients do not have enough internal capabilities to perform the required tasks of their goals, $\exists RC | RC \not\subseteq C_{IN}$. For example in Fig. 1.3, the patient wants to achieve a goal and has 6 capabilities of c_1, c_2, c_3, c_5, c_6 and c_7. The goal requires performing Tasks 1, 2 and 3. Three capabilities of c_1, c_2 and c_3 are required to perform the task 1. For the task 2, c_1, c_4 and c_5 are required, and for the task 3 the capability of c_2 is required. As the patient does not have the capability of c_4, it can not perform the task 2 and consequently can not reach the goal.

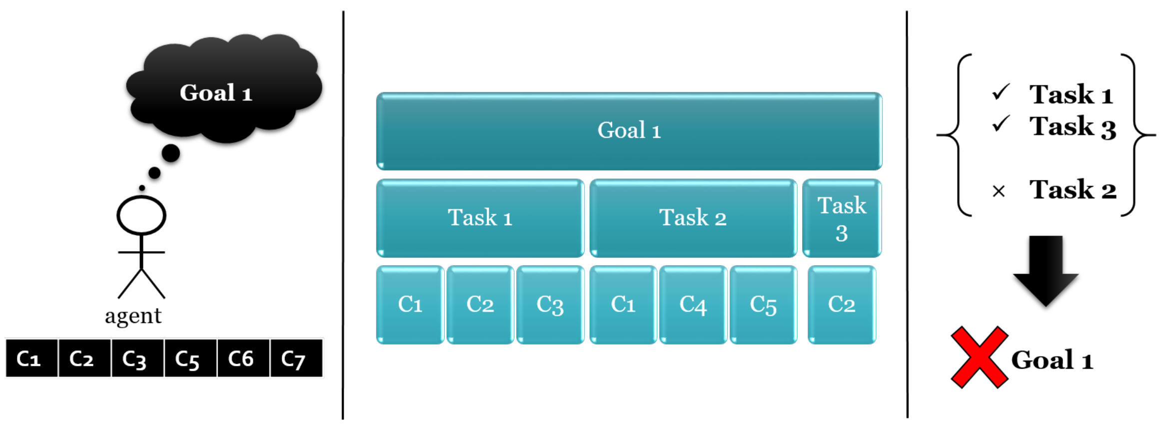


Figure 1.3: An example to illustrate the problem

To cover this weakness, the patient must rely on the external capabilities which are provided by the care providers. Hence, multiple care providers may be needed to support a patient. If we assume that, there is a distance cost between patients and care providers, then the issue can be defined as identifying suitable care providers on a complex network with the lowest cost which is an optimization problem. Meanwhile, lack of the resources is another obstacle here where each care provider can provide a limited number of services to a limited number of patients who may need more than one capability.

In another example, assume a patient needs to see a doctor every week, but he does not have capabilities of speaking and driving. On the other hand, there are some people on the network who like to provide different types of services to the patients. In our example, there is a person who knows sign language and able to drive and take the patient from his house to the doctor. If these people know each other, they can support themselves. But a patient only knows a limited number of people in the society. The main problem is that how an agent can get access to more services in its network to be able to perform more of its daily tasks? Also, how do the people whom the agent knows can help it to achieve its goals? Then, How can an agent extend its sociability as one of the important factors of the quality of life?

In addition, in the previous example, one of the main factors is that a patient may need a long-term care service such as visiting a doctor weekly. In this scenario, is it possible to use the knowledge obtained from the previous experience to reduce the search time of finding care provider/ service provider?

Additionally, a patient's requirements may be changed during the time. For example, assume a child with a chronic disease, who needs some capabilities. His or her required capabilities will frequently be changed when he or she is growing up. Consequently, the question is, how can an agent's capabilities evolve during the process.

1.4 Research Objectives

Our first goal is to describe the system, its domain, and components in an appropriate computable form by an agent-based model. The next objective is to propose an algorithm for the care planning purpose to assist the care providers and patients in the decision-making process. The provided system can provide an opportunity to apply social network analysis techniques to achieve the following goals:

- Enhancing the topology of the healthcare system and increase its performance.
- Improving the quality of services for the patients with similar problems, disorders, and needs.
- Enhancing the human resource allocation's process and reduce operational costs by optimizing the network topology and assigning most appropriate care providers to the patients.

1.5 Research Contributions

This thesis proposes a MAS to model the palliative care systems and improving the quality of services. In addition, a new method is introduced in this thesis to extend agent's capabilities using a social network approach. To the best of our knowledge, it is the first attempt in the field to make a practical computational model to represent the health care systems, especially palliative care and end-of-life care systems.

The output of this research will be an agent-based framework which can be used as a decision support system to recommend caregivers and care providers to patients, based on the required capabilities and resources with the aim of improving their quality of life and services, and reducing the costs.

The performance and functionality of this model are evaluated based on various synthetic networks and scenarios.

1.6 Thesis Outline

The rest of this thesis is organized as follows. In chapter 2, some of the approaches and research works which are related to our proposed model are reviewed. Our proposed model and algorithms, the structure of the agent in this model, and the formal definition of a palliative network are discussed and explained in details in Chapter 3. The experimental setup and parameters that used in the evaluation of our model and the obtained results are presented in chapter 4. Finally, the conclusion, discussions and the future works are discussed, in chapter 5.

Chapter 2

Related Work

In this chapter, the existing research works in the field are reviewed. These works are divided into three parts. In the first part, those research studies that use an agent-based approach to deal with healthcare issues, especially for palliative care and elderly with chronic disease are reviewed. In the second part, some of the well-known and novel methods for extending the agent's capabilities are discussed. Finally, In the last part, several well-known related task allocation algorithms are extensively reviewed.

2.0.1 Multi-Agent based Systems

In recent years, Multi-Agent Systems (MASs) have been widely used to enhance healthcare system. Development of Internet, wireless network and sensors have a significant impact on usage of this approach. The applications of the multi-agent system in healthcare system can be reviewed from two perspectives of application and user domains.

One of the main application is Decision Support Systems (DSS). These systems try to help users in decision-making process using the received data from various sources such as Electronic Health Record (EHR) and sensors. Some other approaches in this field, focus on diagnosis a particular disease such as cardiac disorder [13], Parkinson [8], and brain tumors [11]. Another group of research, aims to monitor the patient remotely. Detecting the critical situation, notifying the doctors when a patient is in an emergency condition, exchanging medical data of patients, and personalizing patients guidelines are some of the features of these research projects [27, 18, 12].

From user domain perspective, various types of users are in the center of attentions[15]. An example of MAS to assist staffs and professionals can be found in [27]. In [29, 32, 2, 8, 14], the authors discussed some of the models which can be used to assist the patients at home. These works can help patients in management of their treatment or decision-making process. But, the models proposed in [24, 11, 13] designed to be used by organizations in order to monitor their patients remotely. However, some of them can be used by more than one group of the user [9, 18]. We discuss some of these approaches with more details in the following paragraphs.

Palliasys [24] is an agent-base system which aims to monitor, analyze and collect information of those patients who need palliative care. The authors proposed a MAS to improve the communication process between patient and doctors in Personal Care Unit (PCU) in a hospital. Their proposed system is able to manage the appointments, give access to the patients medical history, and notify the patients about any changes in their treatment process. In addition, the system provides a framework to introduce a criteria, and other medical information.

In [29], the authors proposed an agent-based architecture to model the patient-centric palliative care system. They defined various types of autonomous interacting agents, such as Patient, Caregiver and Administrator agents. These agents have been divided into two classes of agents that interact with patients (Assistant agents), or interact with other agents (System agents). Their primary objectives are to enhance the communications between patients and caregivers and monitor the patients. In this model, a patient is assigned to an agent which is responsible for keeping patient's information, interacting with other agents for scheduling, and reminding some important tasks to the patients such as taking medications. Additionally, Caregiver agents are responsible to assist Patient agents in the scheduling and reminding tasks. In addition, in their model, one type of Caregiver Agents is Coordinator Agent which is responsible to find a team of care provider in response to the patient's needs. Coordinator Agent send their request to care providers using a Care-flow Management System (CfMS). Moreover, other types of agents such as Monitoring, Scheduling, and Administrator agents have been designed to manage the coordination between the Patient and Caregiver agents.

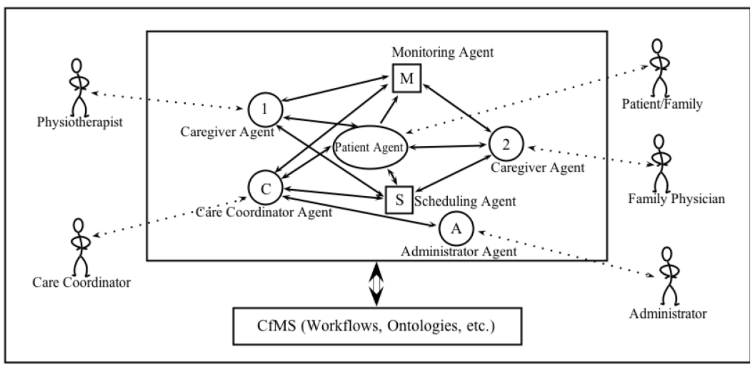


Figure 2.1: An Agent-based Model Home Care[29]

In [32], the authors proposed an IAServe platform. The target of this work is to provide a care plan and suggest some activities based on given information about the patient. The goal of this platform is to improve quality of life of the elderly people by reducing the cost of the services and improving the quality of them. This model consists of four layers which are knowledge Intensive, cloud-based services, agent environment and data repository layers.

Data repository keeps the information about the patient and descriptions of some web services. The care plan is personalized in the knowledge intensive layer by using the information obtained from patient's profile. Cloud service suggests some services to the patient such as weather advice. The agent environment is responsible for managing the patients and adding the care services which are received from the cloud service, in patients care plans.

The Environment layer consists of four types of agents. The Environment Data agent which is responsible to receive data from Yahoo!Weather. Another agent is Service agent which is responsible of monitoring the implementation of the proposed care plans. Each patient is mapped to an agent which is called User agent and performs the proposed services whenever a task from Service agent's is received. The last agent is Maintenance agent which deals with the changes in the healthcare environment, such as updating the information by professionals.

In [14], the authors proposed a web-based MAS system to support patients who require services in their house. Care plan personalization is one of the main features of their proposed system. The plan is designed using the clinical guidelines, and then the system customizes it for each patient. It is a helpful feature especially when patients have more than one chronic medical conditions. Another feature is the architecture which is three-layer structure consists of knowledge layer, data abstraction layer, and Agent-Based layer. Using this architecture makes the model more flexible, reusable and adaptable.

Additionally, in [2], the authors proposed a MAS assistant tool to support Home Care system, and help older adults with chronic disease in their home. Their model works based on the transmitted information from multiple sensors which are set on the patient's body. Each sensor is defined as an agent in the model. They claim that their proposed system is capable of detecting the patient's abnormal conditions and give the adequate emergency suggested and alarms.

2.0.2 Agent Capabilities

The concept of capability in BDI (Belief-Desire-Intention) model was introduced in 1999 [7] to make the agent more adaptable. BDI architecture [5] is a philosophical theory that defines an agent by three components. In this architecture, Belief maintains the agent beliefs about itself or other agents, Desire represents the goals of the agent, and finally, and Intention shows the plans that agent can choose to achieve its goal.

Busetta[7] defined a capability as an identifiable unit with a set of plans, belief knowledge, associated rules and the recursive inclusion of other capabilities. These associated rules consist of visibility rules that show if the events or beliefs are accessible outside of the capability.

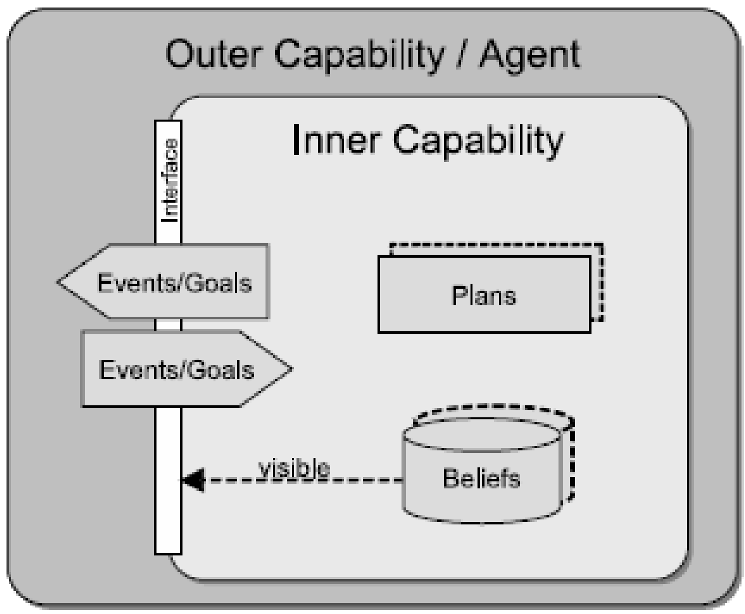


Figure 2.2: Concept of Capability [6]

The capability concept has been studied and extended by other authors to developed its features such as its modularization [6]. In another study [25], the authors defined and formulated the capability in a single BDI agent. In this article, they explored the relationships between capabilities and belief, desire and intention. They also mentioned that their model could be converted to a multi-agent system.

In [1], the authors have been extended the definition of capabilities to facilitate agent to collaborate with other tools or agents. They classified the concept of capability into two classes, include internal capability, and external capability. They formalized and defined the internal capability as those capabilities that agent already has at least one plan to do it. In another word, those capabilities that agent can perform by itself without another agent's help.

The authors also mentioned that an agent needs external capabilities because internal capabilities are not enough for an agent to achieve its goals. Therefore, the external agent's capabilities are divided into two types. Firstly, those capabilities that can be achieved by collaboration with tools in the environment, and secondly, are those that need association with other agents. They also formalized the external capabilities.

In [23], the authors simulated exploiting artifact by the agent and evaluate the impact of social inhabitation on the process of artifact selection. An artifact is a tool in the environment that has some capabilities and can be used by the humans (agents) in order to achieve their goals. They simulated the effects of social inhibition and demands on the artifact selection by using a computational multi-agent model.

In that paper, the artifact selection in the presence and absence of inhibition are tested. The agents have random capabilities and mapped to two separate group. Simply, age is a designed element that shows the amount of influence among agents. Each group has some tasks to do that each task needs a random capability. As a result, this article has shown that the effect of social inhibition in capability selection. Moreover, the effects of demand on group performance have been shown.

In [22], a model is designed with the agents that can exploit the desired artifact toward achieving their goal. Therefore, the agent can improve its capabilities and knowledge about using the proper artifact in order to achieve its goals. Different types of evolutionary computation algorithms have been used in the three levels of experience learning phase of the agents. Genetic Algorithm (GA)has been used for individuals and socials learning. Additionally, both of the Cultural Algorithm (CA) and Multi-Population Cultural Algorithms (MPCA) have been used for social networks. Adaptation strategies have also used to evolve capabilities in MABS.

In this model as shown in fig.2.3, a learning agent has been defined that can learn to exploit proper artifact from the environment. In her dissertation, an artifact can be seen as external capabilities with special abilities that can help the agent to achieve its goals. The knowledge about capabilities plans (select and use plans) of the artifact is stored in the capabilities structure. The Performance Element decides to choose the best artifact by the plans in the capabilities and restriction in beliefs to achieve a goal. The belief space keeps the experience of using unsuccessful artifacts for each capability. After using an artifact, the Critic Element (CE) compares the data from the sensors with performance standard which is predefined standards and send it to learning element. The Learning Element is responsible for improving the capabilities by the help of its learning strategies and the received feedback from Critic Element.

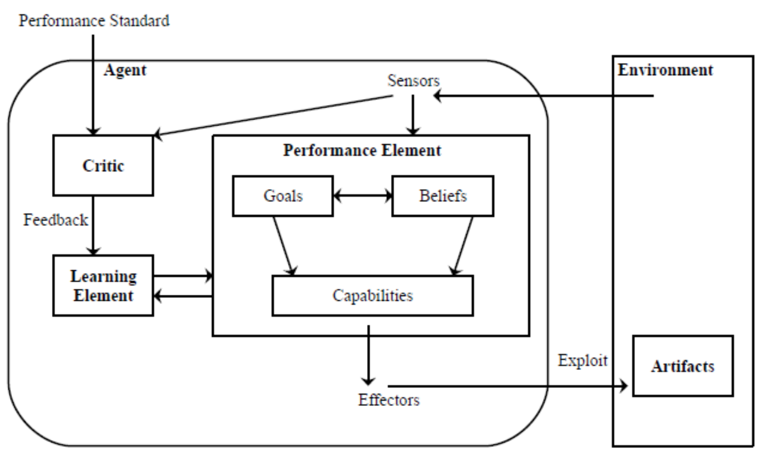


Figure 2.3: An Intelligent Agent Model able to Exploit Proper Artifact[22]

2.0.3 Task Allocation

In [34], the authors proposed a GA algorithm to deal with the task allocation problem. In this model, the algorithm get requirements of each task and try to identify the best set of agents who can perform that task. GA is used to find a near optimal solution for this issue. The authors claim that their proposed algorithm can find a near optimal solution for this type of task allocation problem with a good level of robustness, scalability, stability, and accuracy. A task in their model can be done by a single agent or a team of agents. In their work, a task is allocated to a group of agents that have the best collaboration rate. The assumption is that this group is the most suitable one for the task. Each capability has a weight that shows how an agent ca do the capability perfectly. Therefore, a member of the team which has smaller weight is influenced by the other agent. The method also compared with the Hungarian algorithm for the same scenario.

The authors in [31], proposed a MAS for task allocation problem in a dynamic environment where each task can be allocated to an agent or a group of agents. They provided three algorithms for task allocation and used the concept of synergy to identify the best group of agents for a particular task. The model has been evaluated in three level; agent perspective, team perspective and system perspective. The model achieved 83.68% efficiency in the environment with changeable agents.

In this model, there is no restriction on access to the tasks or agents and all agent can be assigned to all tasks. Each task has its priority which shows the task's interdependency, means that a task may have a prerequisite. If a provider has all the capabilities to do a task, the task would be allocated to it. If no provider can provide a task, the task would be divided into some subtasks, and the system looks for a team of providers. A good team in this paper has been defined as a group of agents with maximum synergy which shows how much good agents can work with other members (agents) of the group.

2.1 Conclusion

As a summary, in this chapter, we reviewed some of the well-known computational models and approaches to study healthcare systems. This chapter shows that these research works mainly focus on providing particular sort of services such as monitoring or diagnosing the disease. However, there is very few research works in the field for enhancing the quality of life of the patient with some sort of disabilities.

Additionally, different types of agent-based models were developed to deal with the task allocation problems. They aim to find the optimal or near optimal solution to reach a particular goal under some constraints.

Furthermore, most of the reviewed MASs are designed to be used and operated by professionals, but are not capable of working in dynamic systems. Meanwhile, they are not scalable and just capable of providing a very limited number of predefined requirements.

We also observe that none of the existing proposed models for extending agents' capabilities used the benefits of social networks. In the task allocation algorithms also, there is very few research works to address the open issues of healthcare in a dynamic environment and processes. Moreover, to the best of our knowledge, none of the existing approaches has addressed the palliative care problem using social network perspective.

We believe that, with the widespread of social networks, it is possible to use its advantages to solving the open problems in the field much more faster and accurate than the traditional approaches. Therefore, a patient can be seen as a social actor in a social network, and social network analysis techniques can be applied to study its role and requirements.

Chapter 3

Multi-Agent Model for Health Care Social System

In this chapter, we present our model to describe the healthcare system and propose a method to deal with the discussed problem. First, all of the agents in our model is seen as a network. This network is defined in the next section. Secondly, we show the agent and its component in details. Then, we show how the components are working with each other. The algorithm, the roles, and responsibilities of agents are discussed in section three of this chapter.

3.1 Network Representation

The system can be mapped to a network consists of a set of agents. The structure of agents will be described in the next section, but these agents are divided into two classes of patients and care providers. Consequently, the network is defined as:

$$N \triangleq (AG^P \cup AG^C) \tag{3.1}$$

Where AG^P and AG^C represent the set of patients and care providers respectively. Each agent is linked to one or more agents which forms a graph G(V, E) where agents are the nodes in the graph and E is the set of links between pairs of agents. Fig. 3.1 shows a sample of care network with six agents. The network can be converted to a graph using the adjacency matrix.

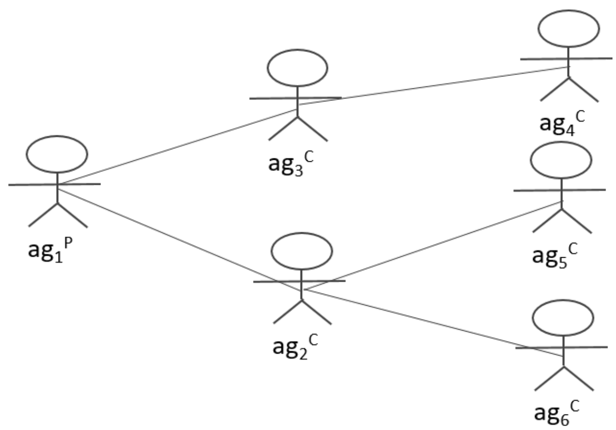


Figure 3.1: A sample care network with six agents

For example, as shown in fig 3.2, we have a network with six nodes, consists of one patient and five care providers. The matrix shows the structure of the graph. it means that the patient agent is connected to the care provider agents with the IDs of 2 and 3. This matrix is an unweighted graph that does not show the level of connection between the agents.

$$\begin{array}{cc} & \begin{array}{cccccc} ag_1^P & ag_2^C & ag_3^C & ag_4^C & ag_5^C & ag_6^C \end{array} \\ \begin{array}{c} ag_1^P \\ ag_2^C \\ ag_3^C \\ ag_4^C \\ ag_5^C \\ ag_6^C \end{array} & \begin{pmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

Figure 3.2: a sample adjacency matrix

However, to increase the accuracy of the modeling, we also consider the geographical distance between the nodes in the network using a given weighted graph. The weight here can be interpreted as a geographical distance cost between agents. For example, a sample network can be represented using the matrix shown in fig 3.3. According to the matrix, the distance between the patient agent and care provider agents are 0.25, 0.50,1, 0.33 and 0.1. It means that, the physical distance between the patient agent and care provider agent number 6 is closer than others. However, assuming the network in this example is the same as the previous example in fig 3.2, there is not any direct connection between the patient agent and this care provider. Therefore, the patient agent can not get service from it.

The distance cost can be defined by a m by m matrix where m shows the number of agents in the network. The weight is a value between 0 to 1 ($0 =< distancecost <= 1$). This weight can be interpreted as geographical closeness of agents in the network.

$$
\begin{array}{cc}
 & \begin{array}{cccccc} ag_1^{P} & ag_2^{C} & ag_3^{C} & ag_4^{C} & ag_5^{C} & ag_6^{C} \end{array} \\
\begin{array}{c} ag_1^{P} \\ ag_2^{C} \\ ag_3^{C} \\ ag_4^{C} \\ ag_5^{C} \\ ag_6^{C} \end{array} &
\begin{pmatrix}
0 & 0.25 & 0.50 & 1 & 0.33 & 0.1 \\
0.25 & 0 & 0.12 & 0.25 & 0.90 & 0.2 \\
0.50 & 0.12 & 0 & 0.85 & 0.45 & 0.7 \\
1 & 0.25 & 0.85 & 0 & 0.32 & 0.17 \\
0.33 & 0.90 & 0.45 & 0.32 & 0 & 0.59 \\
0.1 & 0.2 & 0.7 & 0.17 & 0.59 & 0
\end{pmatrix}
\end{array}
$$

Figure 3.3: a sample weighted graph based on distance cost

3.2 Agent Representation

In our model, all agents have the same structure but with different roles and responsibilities. The BDI model is used to describe them which is shown in the Fig. 3.4. Hence, each agent is defined as follow:

$$AG \triangleq < C, G, B, st > \tag{3.2}$$

Where st shows the status of an agent which can be $\{0,1\}$. If the status is 0, means that the agent is not available. C shows the agents capabilities, B keeps obtained knowledge (belief) perceived from the environment and G determines the goals of the agents. These elements and their structures are discussed in the following paragraphs.

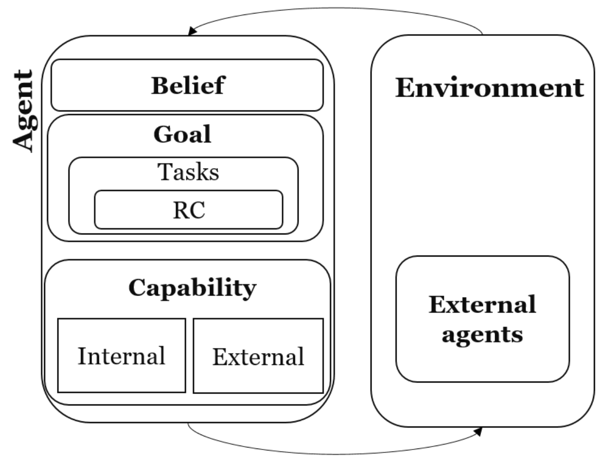


Figure 3.4: Structure of an agent

3.2.1 Capabilities

According to the [1], a hierarchical structure can be used to represent agent capabilities which consist of Internal and External capabilities. The authors in [1], also mentioned that the external capabilities also can be divided into two kinds of capabilities. The first are those that achieved by tools and the second are those ones that can be reached through the other agent's help. We assume the external capabilities as just one class because the agent in our model can use both of the tools and the agent's support. Therefore, each agent in our mode has a list of capabilities including two types of capabilities; Internal and external capabilities that achieve by other agents. Therefore, the capability of an agent is represented as:

$$\begin{aligned} C_{ag \in AG^P} &\triangleq < C_{IN} \cup C_{EX} > \\ C_{IN} &= \{c_{id} | 1 \leq id \leq m\} \\ C_{EX} &= \{c_{id} | 1 \leq id \leq m\} \\ C_{IN} \cap C_{EX} &= \varnothing \end{aligned} \tag{3.3}$$

As mentioned before, each internal capability $c_{IN} \in C_{IN}$ is a capability that agent can execute independently. In our model, we assume that an agent can provide capabilities only when it can do it by itself, so the provided capabilities can be chosen only from the list of internal capabilities when the agent is a provider. Therefore, a capability can be defined as:

$$c_{IN} \triangleq < cid, st, pr, cst > \tag{3.4}$$

Where *cid* is the name of the capability, and *st* determines if the agent has the capability of *cid* to offer or not. Hence it can be 0 or 1. On the other hand, the *pr* determines if the agent wants to provide the capability of *cid* by the associated operational cost of *cst* . So, *pr* value also can be 0 or 1.

On the other hand, an external capability $c_{EX} \in C_{EX}$ are those capabilities that can be achieved by the help of other agents. External capabilities help the agent to keep track of other agents which helped the agent previously in performing some of the missing capabilities. It is defined as:

$$c_{EX} \triangleq < cid, st, EX_{AG} > \tag{3.5}$$

Where, EX_{AG} is a list of agents which can help or provide this capability.

3.2.2 Goals

In addition, each agent has a set of goals which is represented by a multi-dimensional array. Each goal consists of some tasks which must be performed. Each goal can be shown as:

$$g_{ag} \in G_{ag} \triangleq < gid, T_g > \tag{3.6}$$

Where gid is the name of the goal, and T shows a set of tasks which are needed to be executed by the agent to achieve the goal. Each task can be defined as:

$$t_g \in T_g \triangleq < tid, RC_t > \tag{3.7}$$

Meanwhile, to perform each task a set of capabilities are needed. RC is a required capabilities for each task tid and can be shown by a binary array $RC_t =< rc_0, rc_1, ..., rc_m >$.

For example, the figure 3.5 shows the structure of a set of goals for a patient which consists of n goals. For example, for achieving the first goal, task 1 is not required but the second task is required. This task also needs some of the $0 < rc < m$ to complete the task.

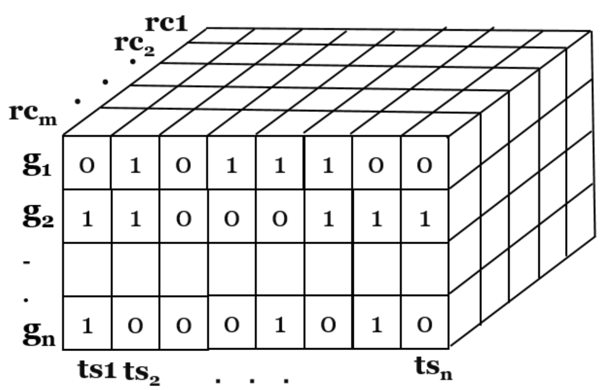


Figure 3.5: A sample of goal for a patient with n goals

3.2.3 Belief

As discussed before, the belief space keeps the obtained knowledge about the environment. We define two different types of knowledge for an agent which are topological and domain knowledge. The belief space is a non-static array, and the obtained knowledge will be added to it. The belief can be defined as:

$$B_{ag} \triangleq < Kn^D \cup Kn^T > \tag{3.8}$$

Where the Kn^T is a topographical knowledge, and Kn^D is the domain knowledge. Topological knowledge is used to store the required information about the patient's neighbors. Therefore, a patient has the partial view of the network and can see just its own direct neighbors(other agent which are connected to the agent directly). The topographical knowledge can be represented as:

$$Kn^T_{ag \in AG^P} \triangleq < Neighbor_{ag}, dcst > \tag{3.9}$$

Where $Neighbor$ shows a list of agents which are directly connected to the agent and $dcst$ shows the distance cost between them. This knowledge will be updated after each iteration, and new neighbors will be added.

Another knowledge is domain knowledge Kn^D which is a temporary knowledge. This knowledge keeps the information about the responses. It can be shown as:

$$Kn^D_{ag \in AG^P} \triangleq < ag^C_{id}, c_{id}, cst > \tag{3.10}$$

Where ag^C_{id} is the ID of a care provider agent which can provide the capability c_{id} with related operational cost of cst. A patient agent uses this knowledge to find the suitable care providers with the lowest operational cost. This knowledge will be updated after each iteration. Same id also will be added after each iteration to the Kn^T_{ag} to connect the patient agent to new agents.

As mentioned before, our model aims to extend capabilities of the agent (patient) by the help of other agents(care providers). We assume that a patient has some Internal capabilities and there are some providers (External agents) in the environment which want to provide some services to support the patient's needs. So, we have two types of agents which are patient agents and care provider agents. Each patient agent has some missing capabilities, and care providers are willing to provide some capabilities to the patients based on their Internal capabilities.

We use a fixed-size binary array to represent the capabilities. For example, assume we have five predefined capabilities, c_1, c_2, c_3, c_4, and c_5 which represent the capabilities of bathing, walking, reading, driving, and socializing. If an agent already has all of the capabilities, then its internal and external capabilities are represented by binary arrays with the size of 5 where $C_{IN} = [1, 1, 1, 1, 1]$ and $C_{EX} = [0, 0, 0, 0, 0]$. Now, assume that the agent is not able to drive. Therefore, the internal capability is changed to $C_{IN} = [1, 1, 1, 0, 1]$.

Patient agents also have some goals which can be completed if all needed tasks can be done. The agent also needs to have some capabilities to perform a task. So, the patient agent with its internal capabilities may or may not complete a task if the agent does not have one of the capabilities.

Algorithm 1 Agent Model to support Palliative Care

Input: graph $G(V, E)$: The structure of a given palliative network;
AG^P: List & characteristics of the patients;
AG^C: List & characteristics of the care providers;
Output: List of the care providers who can support the patients with the lowest cost

```
n ← |AG^P|;
initialize Neighbor_(1...n)
for i ← 1 to n do
    RCE_i ← EstimateReq(G_{ag^i}, C_{ag^i})
    if RCE_i is not empty then
        Kn^D_{ag^i} ← SendReq([Neighbor_i], RCE_i)
        [(Providers, c_id)] ← SelectAg(Kn^D_{ag^i})
        C^i_EX ← {c_id}
        Update(Neighbor_i, [Providers])
    end if
end for
```

As shown in algorithm. 1. The structure of a health care network and characteristic of each agent are given to the algorithm. These characteristic consists of filling the type of the agent (care provider/patient), the patient Goals(G), and the agent capabilities(missed and provided capabilities). Generally, each agent has a list of neighbors which is stored in topographical knowledge (Kn^T) of the agent.

After that, the required capabilities to achieve a goal is estimated as shown in algorithm. 2 and is stored in RCE. Simply, the required capabilities are those capabilities which are needed to perform a particular task to achieve a goal but the agent does not have it on its internal capabilities. RCE keeps a list of all of the required capabilities of a patient agent.

Algorithm 2 Estimate Requirement (for Patient Agent)

Input: G_{ag}:agent goal; C_{ag}: set of capabilities
Output: set of required capabilities to achieve the goals

$Req_{goal} \leftarrow RC_{Tg}$
if $(Req_{goal} \subseteq C_{ag}$ **then**
  $RCE \leftarrow \emptyset$
else
  $RCE \leftarrow RC_{goal} - (RC_{goal} \cap C_{ag})$
end if

Algorithm 3 Care Providers Requirement Estimation

Input: RCE^x_{ag}: set of required capabilities of the agent x

$CP \leftarrow RCE^x_{ag} \cap C_{ag}$
if $CP \neq \emptyset$ **then**
  $SendBack(CP, cst, ag^x)$
else
  $Send([neighbors], RCE^x_{ag} - (RCE^x_{ag} \cap C_{ag})\, x);$
end if

When the requirement estimation process is finished, if RCE is not empty, the patient agent send the list of the required capabilities to its neighbors (care provider agents) and ask them for the support. Then, the neighbors estimate their capabilities as it is shown in algorithm. 3.

As shown in Algorithm 3, the care providers get the required skills and match them with their own capabilities. If they can provide the capabilities, they will send back a reply to the patient and inform it about the type and cost of the support. If they can not provide the capability, they will forward the request to their own neighbors. If the neighbors can provide a part or all of the capabilities they send back a response directly to the patient and inform it about the type and the cost of their support.

When the process is finished, and all care providers sent their feedbacks. The system searches in (Kn^T) for the most appropriate care providers. To find the optimal solution, each requirement capabilities check one by one for each requirement capabilities. Those capabilities with less operational and distance costs are chosen. For each capability, only one care provider will be added.

Next, the chosen capabilities and the corresponded care provider agents are added to the External Capability of the patient. Consequently, if in the future the patient agent wants to perform a new similar task. It does not need to search the whole network, it just looks at its external capability and chooses the suitable care provider.

3.3 Conclusion

In this chapter, we proposed our model and represented the related equations, formulas, and algorithms. We also defined a way to represent the network structure. To create the network, we used the weighted method which is calculated based on the operational cost and distance cost. We also described a BDI agent which is able to represent a patient or a care provider with different roles, tasks, and goals.

In addition, the concepts of internal and external capabilities were defined in this chapter. Meanwhile, the structure of a goal of each agent consists of tasks and the required capabilities for each task has been proposed. Moreover, two types of belief space which are topographical knowledge and domain knowledge to keep the information of network and responses were discussed.

Chapter 4

Evaluation

In this chapter, we evaluate the performance of our proposed model and compare with other methods and report the results. We used a simulated palliative care network as our case study.

In palliative care scenario, there are some patients and care providers in the network. Each person in the society knows some people (e.g.family members, friends, doctors). Between each two people, there is a distance cost which can be described as time or financial cost. As an example, connecting by letter may take more time than connecting by phone. A patient in palliative care has some disabilities like unable to bathing or driving. On the other hand, each patient has some goals such as visiting the family doctor, which needs someone to collaborate with the patient to be achieved.

Each care providers provide some of their capabilities within related operational cost. This operational cost also can be financial cost or time. In addition, each care provider can provide its capabilities to a limited number of patients. As it mentioned, the aim of this dissertation is to find the best provider with minimum operational cost and maximum quality.

In the following paragraphs, we simulate several scenarios to deal with the problem. First, we describe our evaluation setup and metrics and then we report the obtained results.

4.1 Setup

To create a network for Palliative care, we use the LFR social network benchmark in [20, 19]. We generated multiple synthetic networks with 140 nodes(agents), $m = 140$. The following parameters have been considered to generate these networks:

- $\beta = 1$, β set the exponent for the distribution of community size in the network
- $\gamma = 2$: γ set the exponent for the nodes' degree distribution.
- μ =0.2, μ is the mixing parameter which determines the ratio of the number of edges between various communities to the total number of them. The higher number means more complex community structure.
- $D_{Average} = 17$, $D_{Average}$ represents the average degree of each node in the graph.
- $D_{Max} = 50$, D_{Max} set the maximum degree size for each node.

As shown in Fig. 4.1, the generated graphs with LFR benchmark represent the power-law distribution. In addition, they have a high number of cluster coefficient relatively. Meanwhile, the average distance between nodes in all of them is less than four, which represents the small-world effect on the social networks. Consequently, these graphs can represent the key features of real social networks.

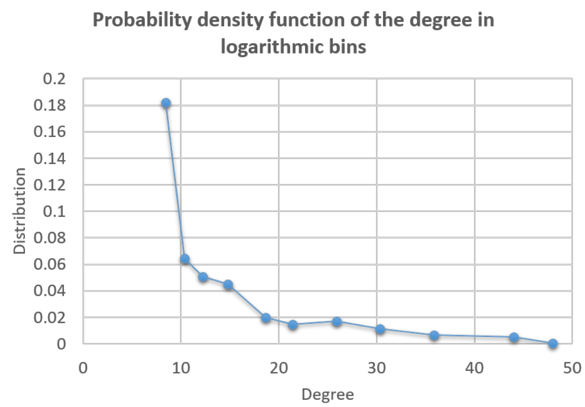


Figure 4.1: Probability density function of the degree in logarithmic bins

Moreover, each agent in this generated networks has approximately 16 neighbors. Some of the agents are not available in each experiment, so, the unavailable agents are not providing our requesting capabilities. The agents have been divided into two parts of care providers and patients. On the other hand, in our experiments, each agent has ten predefined internal capabilities.

Additionally, 1 to 3 of patient agent's capabilities are not available to shows the missed capabilities. In this experience, each patient also has two goals and four goals where each goal can be achieved, if two related tasks can be performed. As it mentioned, in order to complete each task several capabilities are needed. Needed capabilities are chosen randomly.

Furthermore, some of agents are care providers, which want to provide some capabilities. The provided capabilities are selected randomly from internal capabilities of an agent. Each care provider has a special operational cost for each service(capability) that wants to provide. The operational cost is assigned by a random number between 0 and 1 ($0 <= Operational cost <= 1$). Each care provider can provide services to maximum three patients.

4.2 Evaluation Method

As we mentioned, we compared our model with some other methods. The first method is Brute Force model which used for comparison. In Brute Force model, patient agents search for all possible care providers in the network. In This model, only patients sends their requirement capabilities to their neighbors but if a care provider does not have some capabilities care provider agent does not search in its neighbors. In another word, patient agent sends its requirement to all the care provider agents in the environment.

We also used another algorithm (Random) which sends the patient request to a set of care providers that are chosen randomly. The maximum number of care providers in that receive a patient request is 16 care providers. Similar to Brute force model, care providers do not send any requirement to its neighbors or other agents.

Three criteria are used for this comparison. We calculated the required time for each patient to find a set of care providers to cover its requirements. Also, the number of achieved capabilities and the average cost of them are obtained. In some comparisons, We also calculated the number of needed goals of the patient to show after each round how many goals and tasks can be done by the patient without searching on network. From the system perspective, the overall time of the process and the success rate are also analyzed.

We also evaluated our model in the continuous process where a patient agent can used experience about past collaboration with other agent in the next experience. In addition, the neighbors of patient agent will be increased when a capability is added to the agent's external capabilities. We used a dynamic social network that in each experience, some of the agents are unavailable.

In all of our comparison, five types of networks are used with different type of distributions. The distribution of patient and care provider agents in five different networks is shown in following:

- Network with 70 patient agents and 70 Care providers
- Network with 90 patient agents and 50 Care providers
- Network with 100 patient agents and 40 Care providers
- Network with 110 patient agents and 30 Care providers
- Network with 120 patient agents and 20 Care providers

For all of these classes, and all comparisons, ten independent experiments have been done. All of the results are reported in the next section.

4.3 Result

In this section, we discuss the obtained results of evaluating our model's related to performance.

At the first step, we execute all mentioned models ten times with random input. The input consists of different available agents, missed capabilities/ provided capabilities, operational costs/distance cost, and patients goals.

We estimate the success rate of our model with the other models(Brute Force and Random). As shown in Fig. 4.2, our algorithm could provide services (capabilities) to the agents with a high success rate. For example, in the class of 70-70, more than 150 services are received by patients from the care providers while in the random method this is just under 40 services. But compare with Brute Force model, our model can provide only a little bit less than Brute Force model. The results clearly show that our algorithm can help the patients with a high rate of success.

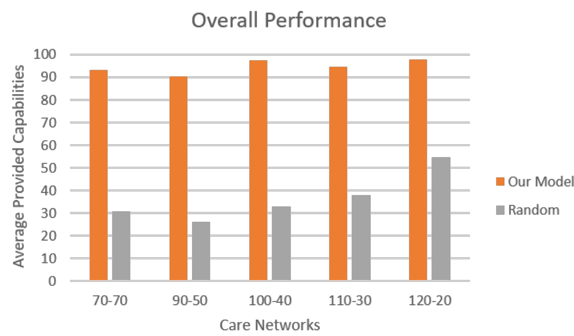


Figure 4.2: Performance Evaluation

As another criterion, we compared the process times of each method which are reported in Fig. 4.3. The process time is an average time consumed by the patient from entering the system (when the patient received its goals) to add a new external agent to its neighbors.

As seen in the graph, our algorithm found the solutions much faster than the brute force search. However, it is still higher than the random search due to the fact that there is not any decision making process in the random method.

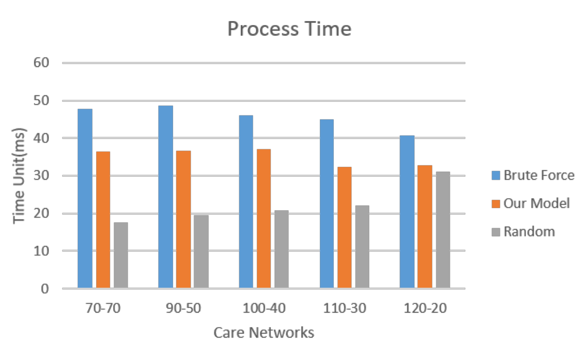


Figure 4.3: Process Time

Then, as shown in Fig. 4.4 the obtained operational costs by the algorithms were analyzed. According to the results, our algorithm received better operational costs, compare with the other methods, which mean that the average operational cost obtained by our algorithm is less than the other approaches.

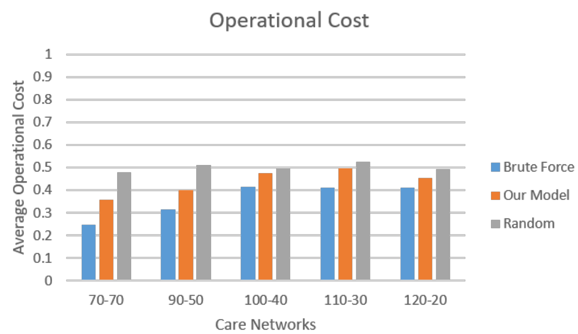


Figure 4.4: Comparison of operational costs

The obtained distance costs for each care networks are also shown in fig 4.5. The results apparently show that our algorithm provides services with less distance cost among the other methods. The distance cost indicates the level of relationships between two agents.

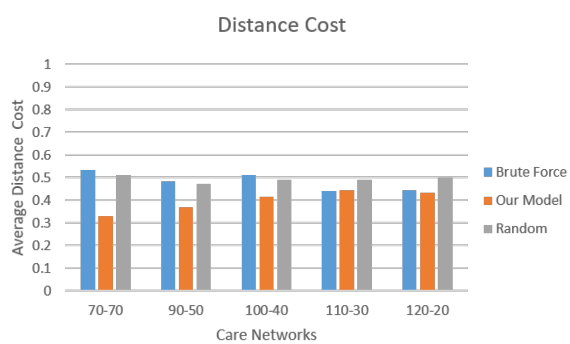
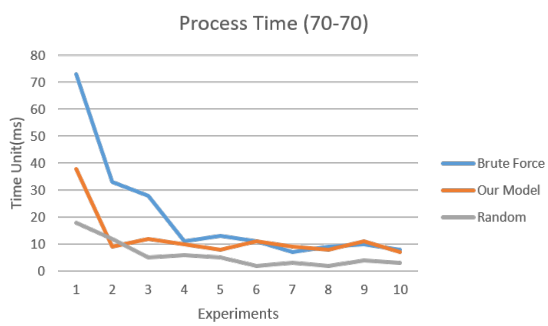


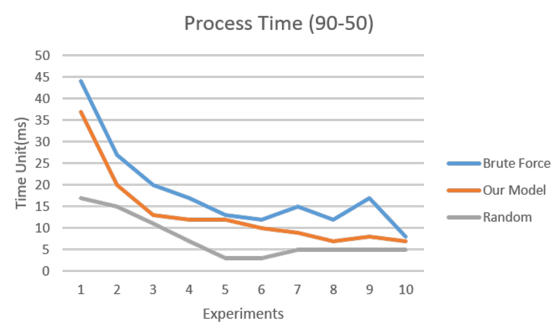
Figure 4.5: Comparison of distance costs

According to the obtained results, our algorithm has clearly a better overall performance and satisfaction rate among the other models.

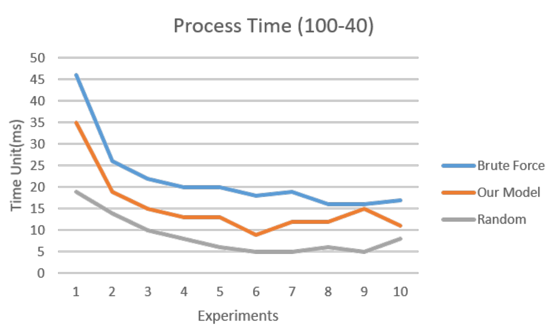
We also simulated the model to see how much our model can help the patient during the time. So, we tested the performance of our algorithm in a dynamic environment. We also compared the performance of these algorithms in a situation that the patients aim to do some goals in each iterations and used its experience of collaborating with other agents in each different iterations. In each iteration, some of the patient agents receive their required services while others do not receive them because of the lack of resources. In other words, in each round, the patient agents may find some care providers which can help them to fill their required capabilities, so in the next round, they may not need those required capabilities. However, as some of the care providers are not available randomly, so it is possible that a care provider is not available in this round. In the following paragraphs, we report the process time obtained by each of the methods in order to achieve the maximum possible tasks.



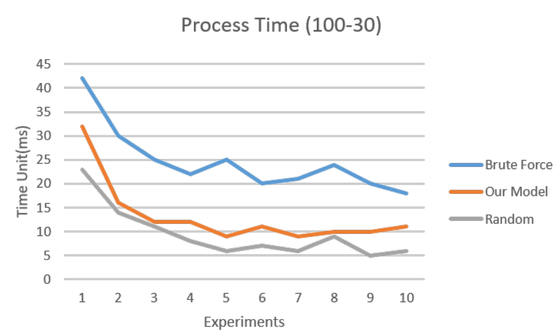
(a) Network 70-70



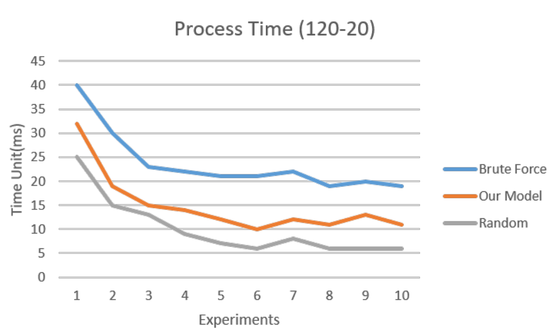
(b) Network 90-50



(c) Network 100-40



(d) Network 110-30



(e) Network 120-20

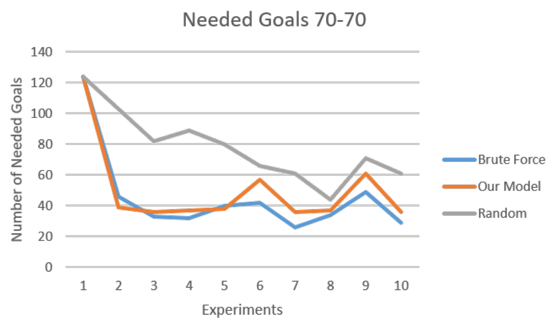
Figure 4.6: Process time in the dynamic environment

As shown in fig 4.6, the process time is decreasing during the iterations due to the fact that, some of the required capabilities are already provided in the previous iterations. According to the results, the patient agents spend less time to find an external resource to cover their missing capabilities by our algorithm than using the Brute Force method. However as discussed before, the random model has the lowest process time among these three algorithms, but the quality of the provided capability is relatively very small.

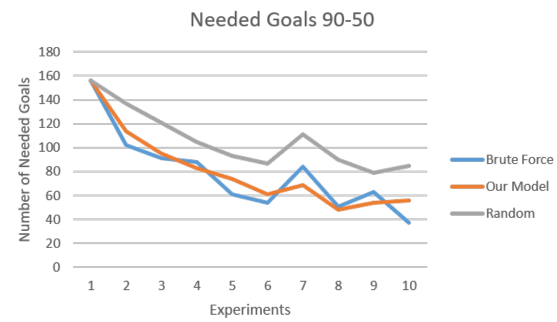
To do the experiment, we assume that, each patient agent has two goals in each iteration. Therefore, decreasing the process time in the next iterations can be interpreted that, the patient agents have obtained the enough external capabilities to reach their goals. In other words, the patient agents can find suitable care providers based on the knowledge obtained from the past experiments, and they do not need to search the whole network again. As shown in the diagram, the required time of our algorithm to do the process is almost half of the required time of the brute force method, while the overall performance is almost the same.

Fig. 4.7 illustrates the overall performance of the algorithms. It shows the number of capabilities which have provided to the patient agents. The brute force method here is our reference because it searches the whole network and finds all of the resources to support the patient agents. This metric can be interpreted as a measurement of the patient agent's satisfaction rate and the overall performance of the system considering the fact that the goal is to provide as much as possible support of the patient agents.

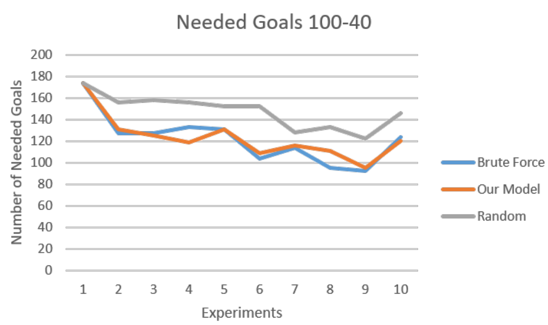
As expected, the random model has the worst performance of the algorithms, while our algorithm has the near optimal performance in all the networks and situations. Which clearly shows the effectiveness of our approach.



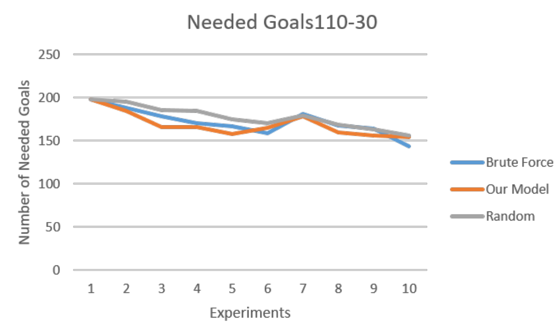
(a) Network 70-70



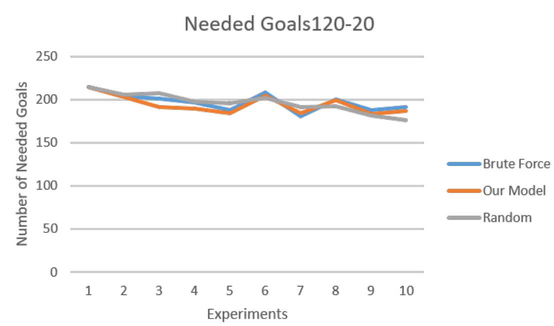
(b) Network 90-50



(c) Network 100-40



(d) Network 110-30



(e) Network 120-20

Figure 4.7: Performance of the algorithm based on the achieved Goals

We also tested the performance of our model when each patient has 50 capabilities instead of 10 capabilities while the other setting has not been changed. The results are reported in the fig. 4.8 to fig. 4.12. The results show that our model is scalable and similar to the previous experiments it has the acceptable overall performance among the others and can find the suitable care providers with the less csost in, the shorter time.

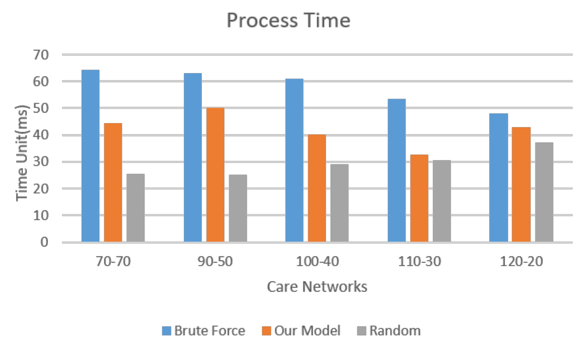


Figure 4.8: Process Time

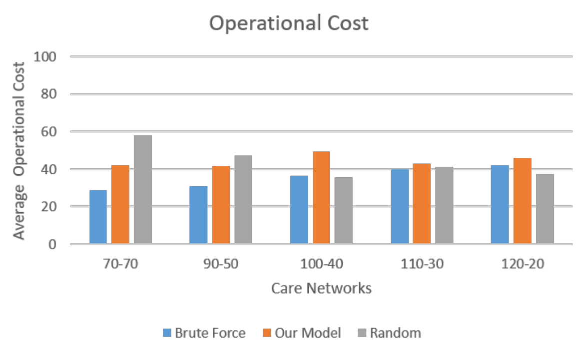


Figure 4.9: Comparison of Operational Cost

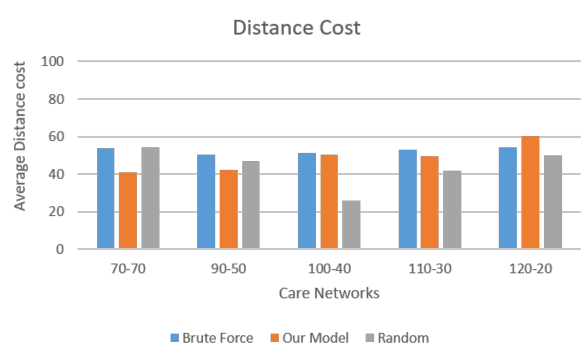


Figure 4.10: Comparison of Distance Cost

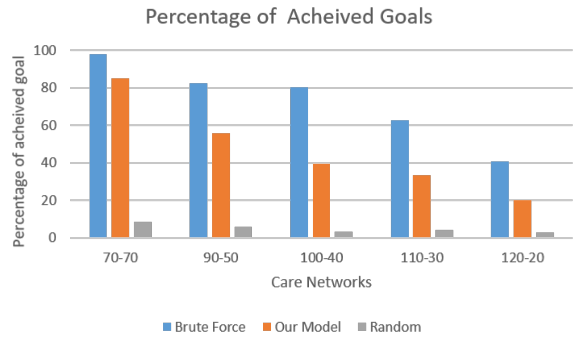


Figure 4.11: Comparison of Needed Goals

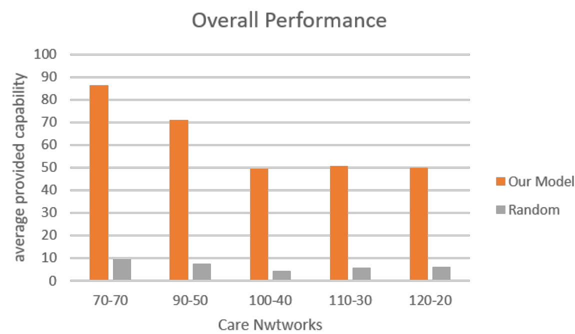


Figure 4.12: Comparison of Provided Capability

4.4 Conclusion

In this chapter, we have evaluated and compared the obtained results from our model with two other methods which are brute force and random. According to the results, our model has better overall performance than Random model while Brute force method can find the better solution but in a very costly time. In addition, with the increase in the size and complexity of the network, the brute force methods will not be practical. However, the results show that our model is capable of finding the near optimal solutions in a very short period of time.

In addition, using our model, the system can give service to mostly all of the patients with the high rate of satisfaction.

Chapter 5

Conclusion

In this dissertation, we proposed a multi-agent base model to extend the agent's capabilities by using the advantages of the social network to minimize the operational costs and maximize the service quality. The model can be seen through two perspectives of patient and system. On the patient view, a patient aims to fill its capabilities by searching its network to find its required services with lower cost in the minimum time. From the system view, the system should be seen as an organization which aims to not only satisfied patient but also care providers.

In addition, we introduced a way to map the palliative care network to a social network. The network consists of several agents who are divided into two classes; patient agents and care provider agents. The patients search in their networks to find a proper care provider agents to fill their missing capabilities and help them to achieve their goals. Each agent as a BDI agent has three components of Belief, Goal, Capability.

Moreover, we introduced a novel algorithm to simulate the palliative care system using our multi-agent framework. In our algorithm, a unique message sending mechanism has been proposed to propagate the patient's requirements to the other agents in the network through the patient's circle of friends.

We evaluated the performance of our model, from both patient and system perspectives. For both of these perspectives the process time, success rate, and the amount of provided capabilities have been calculated. Our proposed algorithm also compared with two different algorithms to show its performance.

According to the results, our algorithm can find the near optimal solution in a very short time in compared to the exhaustive search. In compare to the random selection method also, our algorithm has much better performance regarding the quality of the services.

5.1 Future Work

In the future, we are going to test the performance of our algorithm on the real-world data obtained from the real care centers (e.g. hospices) and compare them with the actual decisions that a human expert can take manually. Meanwhile, exploring the performance of our algorithm on larger networks is our another goal.

In addition, we believe that an evolutionary algorithm can be used to enhance the quality of the agent selection. Hence, we are going to use cultural algorithm as a knowledge based evolutionary method to improve the process of selection.

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