Team Formation in Community-Based Palliative Care

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Abstract—In this paper, a novel knowledge-based evolutionary algorithm is proposed to assemble a team of care providers for patients in community-oriented palliative care. The main objective of this research is to optimize the patient’s care services and human resource allocation process. From a system perspective in palliative care, there exists a group of patients with needs who are not able to perform some of their ordinary life activities due to their limited capability, as a consequence of their disease or disorders. On the other hand, we have a group of care providers who are capable, skilled, and ready to provide a wide range of services to the patients to fulfill those needs. This poses the challenge of assigning members to a team of care providers in an optimal manner to help the patient satisfy their needs, while taking into consideration the communication, distance and contact costs. To deal with this problem, we propose a novel algorithm based on a cultural algorithm (CA) as the basis for our model for assembling an optimal team of care providers. The overall goals are to minimize the costs and increase the patient’s satisfaction rate. We have evaluated our model using multiple synthetic networks and conducted comparative analysis with other existing methods. The results show that our proposed model can overcome the shortcomings posed by the existing approaches.

Index Terms—Team Formation, Palliative Care, Optimization, Cultural Algorithms, Evolutionary Algorithms

I. INTRODUCTION

In recent years, it has been observed that geriatric populations are growing rapidly around the world. According to the UN [1], the number of individuals aged 60 years and over is projected to grow from 901 million in 2015 to 1.4 billion in 2030, which is a drastic 56 percent increase. In addition, it is projected that the global population of elderly people will reach 2.1 billion by 2050, accounting for approximately 20 percent of the world population.

Due to aging, the risk of chronic diseases, social isolation, depression, and fragmented care increases, along with other health related problems. This results in a poorer self-perceived quality of life and an increased dependence on health care services for these individuals and their families. Consequently, the need of developing innovative solutions to support triple value healthcare (Personal, Technical and Allocative) must be considered as a critical issue for improving the quality and delivery of healthcare services [2]–[4]. The Personal value refers to the fact that, the decision making process is carried out based on the individual patient’s values. Meanwhile, according to the Technical and Allocative values, the resources must be allocated and utilized optimally and equitably. It has been shown that improving health and overall well-being among elderly people can be achieved through: (1) enhancing their social support networks and (2) giving them a voice, and choices to make key decisions and direct their own care.

In recent years, person-centric and community-oriented palliative care systems are in the center of attention, to provide support for aging and other related challenges. Palliative care is a type of health care which focuses on improving the quality of life of individuals who are living with life-threatening illnesses, specially with chronic diseases such as cancer, cardiac disease, kidney failure, Alzheimer, ALS, and MS. The primary goal here is to provide various support services to help patients maintain an active life and dignity, while in some cases it may also positively influence the patients’ prognosis and the course of illness. It also provides the patients families with support, to help them better cope with the situation.

This care system uses a team approach to address the needs of patients and their families. In fact, a multidisciplinary team of healthcare professionals, volunteers, family members and friends work together to achieve a common goal of providing the optimal care services for a patient. This team forms a social circle of care for the patient. In this paper, we propose a novel computational evolutionary model to form such a team using members among a given palliative care network.

Generally in palliative care, we have two groups of individuals; patients who generally are not able to do some of their ordinary routine tasks, and care providers who are ready to offer a wide range of services to the patients, to cover their disabilities and support them with leading a normal life. However, each care provider has limited capabilities and can provide special type of services, while only having the capacity to support a limited number of patients. On the other hand, there are several barriers such as geographical distance, communication costs, time availability, etc., which make this process more complex.

In this study, since it is inherent that palliative care networks have a social structure, we are going to approach it from a social network point of view. Consequently, we will have a network of care providers and patients. Assuming the care providers are experts in providing a limited number of services...
and the patients need those services, making the social circle of care for each patient in an optimum manner can be seen as a team formation problem in social networks. In fact, based on the structure of the network, and relationship among the social actors in the network, the best team of support/care can be identified. Forming high-performance teams is very important, because the success of the care system is depend on their performance specially on how well the team members communicate and collaborate with each other and how quickly they can be available for offering the required services. Additionally, other factors such as their availability, geographical proximity and contact costs must also be considered for team formation. In real scenarios, taking these factors into account will lead to recommendation of a high performance team of care who can help a patient get back to leading a normal life.

In this research work, we assume that each patient has a profile which shows his/her capabilities. Capability here means the ability to do a task. The profile also determines the number and the type of the capabilities that a patient does not have, but is still required for a particular task. On the other hand, care providers also have a profile which represents the type and the number of services that they can provide. Considering the distance, communication, and contact costs, we can map the whole care network to a weighted graph. Hence, the problem can be defined as identifying the best team of care (among all the care providers) who can support a patient by offering his/her required capabilities in the most cost effective manner. Moreover, at a system level, the challenge is to identify the optimal configuration of teams that will support as many patients as possible.

As the problem is an NP-hard problem, we are proposing an evolutionary model based on the Cultural Algorithm (CA) to tackle it. CA is a knowledge-based evolutionary model which extracts different sources of knowledge from the best populations in each iteration, and uses them to guide the search direction to reach the near-optimal solution. In this research work, we keep track of the best solution of each generation and extract knowledge from them to form the situational knowledge. Then we use this knowledge source to identify the suitable team of care. For the fitness function we use a method proposed in [5], [6] to calculate the shortest path between the nodes.

The rest of the paper is organized as follows: In the next section, we briefly review the related works. After that, in section 3, we discuss and present our proposed model in detail. Evaluation and analysis of our model’s performance is discussed and reviewed in section 4, and finally we will have a conclusion section.

II. LITERATURE REVIEW

Due to the increased importance of teamwork in the management and healthcare settings, researchers have started to examine the value of team formation [7]. However, only a small number of literature have focused on computational models for palliative care systems. In this section, we briefly review some of the recent research works categorized into three main related approaches: palliative care, team formation and evolutionary algorithms in health systems.

A. As a novel approach in palliative care, an agent based model to improve the quality of service was proposed by the authors in [8]. They examined the method of assigning care providers in order to achieve the patient’s goal. Based on contact costs and resource limitations, they worked on developing a framework for finding a group of suitable care providers to satisfy the requirements from patients. Their proposed model exhibited a reduction in operational costs and improvements in the quality of service [8].

The authors in [9] explored the challenge of balancing the physicians estimated prognoses with the actual care received versus the patients personal wishes. They addressed this using Deep Learning and Electronic Health Record (EHR) data to predict the all-cause mortality of a patient within the next 12 months, enabling the care team to take proactive measures towards reaching out to provide palliative care to such patients.

The authors in [10] proposed an agent-based architecture to facilitate the communication and collaboration among the patients and care providers. Moreover, the authors of [11], [12] used both Multi-Agent Systems, and Information and Communication Technologies to improve the management of the clinical data of palliative care patients. In addition, authors of [13]–[16] used multi-agent system to handle patient care system.

B. Social Network Team formation in health care networks is quite complex. The bulk of the literature on health care teams have focused on team functioning and performance. The authors in [17] proposed a method of forming a team of palliative care network members, and emphasized the importance of collaboration among the members of the team. In addition, the authors in [18] explored the issues arising from challenges in communication among interdisciplinary palliative care team members. The authors in [19] analyzed how conflict develops among team members and explored several approaches to conflict resolution.

None of the models proposed were computational models. Therefore, various applications have been examined within research works which proposed a team formation problem using different approaches in social networks. As described in the previous section, palliative care networks can be considered as social networks. In the area of social networks of experts, much research has been conducted to date.

The authors in [20]–[22] explored the team formation problem in the operational research community using branch-and-cut, genetic algorithms, and the Fuzzy inference approach respectively. However, the social structured graph among team members was not taken into consideration. Therefore, there was no survey or analysis of the effectiveness of collaboration among them.

The authors in [23] explored the team formation problem by analyzing the connectivity between individuals in a social structured graph, and used the communication cost function to evaluate the effectiveness of the collaboration among them using enhanced Steiner algorithms.

The authors in [26] improved the cost function in [23] and introduced the concept of a leader in team formation and explored its significance.

The authors in [27] explored this problem by only using work load balances between team members using an approximation algorithm. Then in [28] they examined the same problem with the addition of the communication cost factor. In reality, when individuals are employed on projects, a compensation is generally expected, with the exception of volunteering roles.

The authors in [6] used personal cost combined with communication cost to form a team of experts using an approximation algorithm. Later in [29], the team formation problem was examined with consideration for the expertise level of each member and their personnel cost.

Furthermore, the authors in [30] introduced the concept of project profitability. Using a cluster hiring approach, they modeled the formation of the team of experts, hired to maximize profitability within a given budget.

The authors in [31] examined a method to calculate the communication cost among the team, by using parameterized complexity analysis. The authors in [32] modeled teams as hierarchical structures to explore the ubiquitous nature of teams in real commercial and open source projects.

C. There is limited literature on the use of evolutionary algorithms on the team formation problem. The authors in [21] applied a genetic algorithm to choose team members and project managers, using a fuzzy inference system to calculate knowledge competence for the selection of the project manager. Additionally, the authors in [33], [34] also explored forming a team of experts using a genetic algorithm.

In [35], the authors used a collective intelligent index to evaluate the expertness of each team member, and applied a genetic algorithm to find an optimal solution.

The authors of [36] took a novel approach by considering the geographical location of each member of the team using a genetic algorithm. Furthermore, the authors in [5] applied a cultural algorithm to produce team of experts for various projects.

There is limited literature exploring the team formation problem in a healthcare setting. However, there is literature exploring the use of evolutionary algorithms to target various challenges in healthcare. In [37], the authors applied a genetic algorithms to handle the constraints related to workload balancing and multi-period planning. They also applied the principles of the robust optimization approach in a healthcare setting.

The authors in [38] used genetic algorithms for health planning. Based on the emergency cases and age related demographic factors, they found the optimal method of allocating ambulance services within a geographical locale.

To the best of our knowledge, no prior work has been carried out to explore the team formation problem in a healthcare system using cultural and genetic algorithms. Therefore, in this paper, we propose a framework to deal with the problem of team formation in community-oriented palliative care using cultural and genetic algorithms. The main objectives are to minimize the costs and increase the patient’s satisfaction rate.

III. PROPOSED MODEL

This section discusses our knowledge-based evolutionary model which is based on a cultural algorithm (CA), to find the best team of care providers for a patient.

A. Cultural Algorithm (CA)

As shown in Fig. 1, CA is a dual inheritance evolutionary system consisting of population and belief spaces. During the optimization process, different sources of knowledge can be extracted from the best selected individuals of each iteration, which are then used to reduce the search domain and guide the search direction. [39], [40].

![Cultural Algorithm Framework](image)

Fig. 1. Cultural algorithm framework

Similar to other evolutionary algorithms such as genetic algorithms (GA), an individual here means a possible solution for a given problem. Therefore, a population is a group of generated individuals in each iteration. First, the initial population is generated randomly. Then the performance of each individual is measured using a fitness function. Consequently, a group of individuals that have better relative fitness values are selected. In CA, different sources of knowledge (e.g., Normative, Situational, Historic, etc) will be extracted from this selected group. The assumption is that, understanding the knowledge behind their good performance can help us to generate a better population in subsequent iterations. Hence, a belief space is designed to store the extracted knowledge. In the next iteration, in addition to performing a crossover or a mutation, the CA uses the knowledge to guide the direction of the search and accelerate the evolution. The search process continues until the termination criteria is met. At the end of the process, the individual with the best fitness value is selected as the final solution for a given problem.

Algorithm 1 shows our proposed method for finding the best set of care provider teams for the patients in palliative care.

The main components of our model are: representations, the
input: graph \( G \) as a network of patient and care providers; \( RC \) as a set of required capabilities of patients; list of available capabilities provided by care providers (CP) 
output: teams of care providers for all patients 

\[
\begin{align*}
1: \ n & \leftarrow |\text{population}| \\
2: \ gs & \leftarrow \text{number of iterations} \\
3: \ t & \leftarrow |\text{selected population}| \\
4: \ elite & \leftarrow \text{number of elite individuals} \\
5: \ Pop (1...n) & \leftarrow \text{generate random individuals} \\
6: \ for \ i \leftarrow 1 \ to \ gs \ do \\
7: \ \text{if} \ \text{random()} \leq 80\% \ \text{then} \\
8: \ \text{else} \\
9: \ \text{end if} \\
10: \ \text{for} \ j \leftarrow \text{elite} \ to \ n \ do \\
11: \ \text{if} \ \text{random()} \leq 80\% \ \text{then} \\
12: \ \text{else} \\
13: \ \text{end if} \\
14: \ \text{end for} \\
15: \ \text{end for} \\
16: \ \text{solution} & \leftarrow Pop_1
\end{align*}
\]

fitness function, and the belief space structure, which will be reviewed in the next sections.

B. Representation

This research paper considers three main entities (patient, care provider, and individual) which must be defined formally in advance. Similar to the model proposed in [8], each patient is represented by a binary array with a fixed size of \( m \), where \( m \) is the number of capabilities. Each cell of the array indicates a predefined capability \( c \), where the value is 1 if the patient has that capability, and 0 otherwise. For example, \( P_1=[0,1,1,1,1,0] \) represents a patient with the index id of 1, who requires the two capabilities \( c_0 \) and \( c_5 \), where \( c_0 \) may represent the ability to drive, and \( c_5 \) can represent the ability to walk.

A care provider also is represented by a fixed-size binary array similar to the patient. The only difference is that, if a value in a cell is 1, it means that the care provider can provide that capability. In addition, each care provider has a maximum capacity for providing services, which has to be set in advance. For example, each care provider can provide a service to a maximum of 5 patients.

Finally, to represent an individual (a candidate solution), we use an array structure with \( s \) cells. The length of the array is equal to the total number of required capabilities. Let \( RC = \{RC^{P_1}, RC^{P_2}, ..., RC^{P_n}\} \) represent a set of required capabilities for all patients (P), where \( n \) is the total number of patients in the network. Then, \( RC^{P_i} = \{(r_{c_0}, ..., r_{c_m})| r_{c_j} \in \{0,1\}\} \). For example, as shown in Fig. 2, if there are three patients in the network and the total number of required capabilities is five, the size of the individual array, \( s \), is equal to five. The first two values are the required capabilities of patient 1 (\( c_0\&c_5 \)), the next two are the needed capabilities of patient 2 (\( c_4\&c_5 \)) and the last cell is the required capability of patient 3 (\( c_1 \)). The value of each cell is the index of a care provider selected from the set of available care providers who possess those capabilities. In fact, these sets are generated in the initialization phase, hence for each capability, a pool of care providers that can provide that capabilities are created.

For example in Fig. 3, we have three care providers, CP1, CP2 and CP3. Care providers 2 and 3 can offer the capability of \( c_0 \), while care provider 3, is the only provider who offers capabilities of \( c_1 \), \( c_2 \) and \( c_3 \). In addition, capabilities of \( c_4 \) and \( c_5 \) are also provided by care providers 1 and 3. According to the previous example shown in Fig. 2, the first patient needs the two capabilities of \( c_0 \) and \( c_5 \), the next patient requires the two capabilities of \( c_4 \) and \( c_5 \) and the last patient needs just the capability of \( c_1 \). Consequently, three random individuals or potential solutions for this problem are illustrated in Fig. 3. According to Individual \( i \) which is generated randomly, CP2 and CP1 form the care team for patient 1. CP1 is also responsible for supporting patient 2, and care provider 3 is assigned to assist patient 3.

As shown in this example, various types of teams can be generated using this individual representation method. However, not all of the teams generated represent the optimal solution. Consequently, we have to evaluate the performance of the solutions using the fitness function.

C. Fitness Function

As mentioned previously, our model uses a weighted graph to show the relationship among the social entities. The weight
here is calculated based on the three groups of costs.

The first is the communication cost, denoted by Ccost, which represents how easily each pair of people can interact with each other. The value is between 0 and 1, with a lower value indicating a better level of communication between a pair of people.

Another group is the distance cost, denoted by Dcost, which refers to the geographical distance between the social actors. Similar to the previous cost, the value is between 0 and 1 and a lower value indicates an increased chance of cooperation.

The last one is contact cost, Tcost which shows the level of productivity of a social entity. The value is again between 0 and 1 but our goal is to maximize this value.

To measure the performance of our algorithm, we are using the following fitness function which is based on the formula proposed in [6]:

\[ F(I) = \sum_{i=1}^{n} F1(TP_i) \] where \( TP_i \) is a generated team for the patient \( i \).

\[ F1(TP) = \lambda \text{CommunicationCost} + \beta \text{DistanceCost} + \Gamma (1 - \text{ContactCost}), \] where, \( \lambda, \beta, \) and \( \Gamma \) are balance factors.

Given a team TP of care providers for a patient: \( \{(c_1, CP_1), (c_2, CP_2), \ldots, (c_m, CP_m)\} \), the sum of distances of TP with respect to Ccost, Dcost and Tcost among the pair of social actors is dened as

\[ \text{CommunicationCost} = \sum_{i=1}^{n} \sum_{j=i+1}^{n} Ccost_{i,j}, \]

\[ \text{DistanceCost} = \sum_{i=1}^{n} \sum_{j=i+1}^{n} Dcost_{i,j}, \]

\[ \text{ContactCost} = \sum_{i=1}^{n} \sum_{j=i+1}^{n} Tcost_{i,j}, \] where \( i \) and \( j \) are indexes of a pair of social actors in the network.

D. Belief Space

Our approach to make the belief space, which is a knowledge-based repository, has been inspired from the belief space formation model proposed in [41]. It is defined as the transpose matrix of the selected individuals. Let a selected individual be defined as \( SI_i = [TP_1, TP_2, \ldots, TP_n] \), Now, assuming the number of the selected individuals in each iteration is \( t \), the selected population can be defined as follows:

\[
SP = \begin{bmatrix}
SI_1 \\
SI_2 \\
\vdots \\
SI_t
\end{bmatrix} = \begin{bmatrix}
TP_1^1, TP_1^2, \ldots, TP_1^n \\
TP_2^1, TP_2^2, \ldots, TP_2^n \\
\vdots \\
TP_t^1, TP_t^2, \ldots, TP_t^n
\end{bmatrix}
\]

Thus, the belief space is defined as \( BS = SP^T \):

\[
BS = \begin{bmatrix}
TP_1^1, TP_2^1, \ldots, TP^n_1 \\
TP_1^2, TP_2^2, \ldots, TP^n_2 \\
\vdots \\
TP_1^n, TP_2^n, \ldots, TP^n_t
\end{bmatrix}
\]

In other words, for each capability (a row of the BS matrix), the BS matrix contains the list of care providers who have previously appeared among the selected individuals.

Assuming the optimal solution can be generated by using the extracted knowledge from the best individuals, in the subsequent iteration, the algorithm generates a new set of individuals by reading the data from the BS matrix and not the pool of care providers. As a result, we expect to observe a reduction in the size of the search space in each subsequent iteration.

IV. Evaluation

This section reports the performance evaluation of our model.

We have taken into consideration 4 different synthetic social networks (i.e. 25, 50, 75, 100 nodes), by grouping patients and care providers using various ratios such as the following:

1) 25 percentage of patients to 75 percentage of care providers, where care providers can provide a maximum of 3 services at a time
2) 30 percentage of patients to 70 percentage of care providers, where care providers can provide a maximum of 4 services at a time
3) 50 percentage of patients to 50 percentage of care providers, where care providers can provide a maximum of 6 services at a time

The networks are generated based on LFR benchmark for generating social networks [42], [43] with the default setting. In addition, Communication, Distance and Contact cost have been assigned to the network randomly.

The random approach has been used as a base model for comparison. The random approach involves randomly assembling a team of care providers. The fitness value obtained from it is used to compare against the fitness values obtained from our Cultural algorithm, and a Genetic algorithm. Authors tested our model on a system with the following specification:

1) Installed memory (RAM): 16 GB,
2) Processor: Intel Core i5 CPU @ 2.50 GHz.
3) Java was used to develop the experimental model.

Each experiment has been conducted 5 times independently, to find the average fitness values. The fitness values has been calculated using the fitness function based on the weighted importance of the cost parameters \( \alpha, \beta, \) and \( \gamma \), which were assigned the values of 0.6, 0.3, and 0.1 respectively.

Figures 4, 5 and 6 exhibit the comparison between the fitness value against different network sizes, tested using various algorithms such as a cultural and genetic algorithm, and also using a random approach. As shown in Fig. 4, when 25% of the population are patients, and the rest are care providers, our algorithm can find a near optimal team of care providers with the fitness values of 14.12, 16.61, 20.33, 29.03, when the size of the network ranges between 25 to 100 nodes. The fitness values obtained using the genetic algorithm and through the random approach perform relatively weaker than our proposed algorithm.

Fig. 5 represents the results obtained for a network consisting of 30% of patients. We can observe the similar patterns between our approach and the other methods. For example, when the fitness value of our model is 31.44 for a network with 100 nodes, the value is 35.85 and 47.38 for the genetic and random approaches respectively. This exhibits approximately
According to the results, our proposed model and algorithm showed an overall better performance in comparison to the other algorithms tested to find a near optimal team of care providers for the patients in a community-based palliative care network.

V. CONCLUSION

In this paper, we proposed a novel approach of assembling a team of care providers for palliative care patients in a community-oriented setting. Our model consists of two primary social entities, patient and care providers, who interact with each other in a social network context. The patients require some support capabilities to lead a normal life style and the care providers offers these capabilities demanded by the patients.

We took into a consideration three different cost variables, communication, contact, and distance costs. The overall goal of our research was to minimize the costs and maximize patient satisfaction. We developed a model using a knowledge-based evolutionary algorithm to optimize the resource allocation and team generation processes in order to provide patients with added value in the form of quality service delivery and an increased quality of life.

The results obtained from our evaluation indicate that, our model is more effective at obtaining the near optimal team formation solution relative to the other algorithms currently proposed in literature within the field.

In future we are going to enhance the algorithm and validate its performance against clinical data. In addition, we plan to expand the experimental scope and take additional parameters into considerations.

REFERENCES
