Using Genetic Algorithms for Group Activities in Elderly Communities

Juan José Hernández[1], Angelo Costa[2], Elena del Val[1], Juan M. Alberola[1], Paulo Novais[2], Vicente Julian[1]

[1] Universitat Politècnica de València. D. Sistemas Informáticos y Computación
juahermo@fiv.upv.es, {jalberola, edelval, vinglada}@dsic.upv.es
[2] Centro ALGORITMI, Escola de Engenharia, Universidade do Minho, Guimarães
{acosta, pjon}@di.uminho.pt

Abstract. This paper proposes a model for group formation in elderly communities using Coalition Structure Generation Problem implemented by Genetic Algorithms. The model parameters are physical requirements, preferences and social relationships, being the model able to learn from each execution and improve the future configurations. The results show near-optimal solutions to all proposed scenarios, beating greatly the computational time of CPLEX.

Keywords: Genetic algorithm, group formation, elderly activities

1 Introduction

Currently, collaboration is essential for successfully achieving any type of goal. We can simply observe the growing importance of concept of business teams in the literature. But this is not the only field where teams, groups, coalitions or partnerships are being used. For instance in education, educational organizations have shown a growing interest in shifting towards teaching paradigms that promote teamwork [2, 1, 3]; in sports competitions, it is well know the importance of building and managing a team to achieve success; and in other fields, such as science, many of the most important results arise from the formation of working groups and their collaboration.

In general, any task with hints of complexity require the collaboration of more than one individual. It is essential to current technology the ability of giving support to the needed processes of formation and management of groups or coalitions with the aim of maximizing the utility or expected benefit.

In this sense, agent technology, although still immature in some ways, allows the development of systems that support the formation and dynamic management of these teams. Many tasks cannot be completed by a single agent because of limited resources or capabilities, even if the task can be done by a single agent, the performance may be too low to be acceptable. In these situations, agents may form groups to solve the problem or accomplish the task by cooperation. This work is focused on the formation of teams in order to do some specific task.

Traditionally, allocating agents into optimal groups has been a field of study for coalition formation [20, 19, 13]. Many coalition formation algorithms focus on optimally dividing coalitional payoffs [6, 17, 21], which are the resulting benefits from carrying on a task as a group.

Genetic Algorithms (GA) have also contributed to the state-of-art in group formation. They are general optimization and learning algorithms based on the evolutionary processes found in the nature. Candidate solutions for a problem form the genetic population of the algorithm, which gradually converges towards high quality solutions by applying genetic operators like mutation and crossover. GA's can be used as an implicit learning and adaptation mechanism in environments where dynamics and structure is also uncertain. This is perhaps what makes GA an adequate approach to group formation problems, since they can be used to learn and adapt both to the different needs and goals of the group's members.

In this sense this work proposes the use of GA in order to solve a specific problem of group formation. Concretely, the proposal has been used to analyse which is the best way to organize older people into activity groups in elderly communities (e.g. nursing homes, day-care centres). Different studies [11, 14, 7, 15, 4, 5, 12, 10] have shown the benefits of a constructive group activities programme for the elderly, increasing their happiness levels and wellbeing. In most elderly communities exist the figure of activities manager, typically assumed by a psychologist or a registered nurse, whose task is to create a list of activities that please the elderly communities' users (care-receivers). An usual issue is the lack of novelty and low significance of the events, leading to bored and unengaged care-receivers. Caregivers should be able to arrange activities that relate to the care-receivers, e.g., likes, health condition, background. Exploiting the social interaction is key to keep a harmonious environment, thus it is essential to please the largest number of care-receivers [18]. The issue is that finding activities that please everyone is rather difficult and most of the activities that do that are ones that require little effort by the care-receiver (like watching television) defeating the goal of promoting active aging through playful psychological and physical activities.

One possible solution is to part the community into groups, being the participants related between them (likes, health condition, friendship), performing activities that are suited to them, optimizing the overall satisfaction of the community. The issue with this solution is that it is a hard problem to find suitable associations between the users. For instance, from the three areas (likes, health condition, friendship) the values can range from love to hate, thus one care-receiver may love another but hate every activity that the other likes, which may eventually lead to unhappiness of the care-receiver in the long term. By using technological helpers the task can be eased by performing the grouping task.

This idea emerged from an issue encountered in the iGenda platform [8, 9]. When in a specific environment where the care-receivers were forced to interact with other care-receivers the iGenda was not able to provide events suggestions in a fashionable time. The complexity of the task and specificity was not initially foreseen thus the iGenda was not designed for this task. The aim of this paper is to treat this issue.

This paper is structured in the following way: section 2 presents the proposed model and the problem definition; section 3 presents the genetic algorithm design, with equations and examples that help to envision the development; section 4 present the experiments and the results of 4 scenarios execution; and finally section 5 present the conclusions.

2 Proposed Model

To make a proper planning of care-receivers allocated per activity during a long period of time (i.e., semester) several parameters should be considered: (i) the physical condition of care-receivers and the requirements of each activity to be performed; (ii) the preferences of care-receivers about activities, to improve their degree of satisfaction; (iii) the friendship relationships of each group.

The most of the nursing homes lack the appropriate number of staff, thus most of the staff is overworked. Another factor to be considered is that the number of activities the nursing homes can offer is limited, so residents have to repeat activities. The use of computational systems that facilitate the activities scheduling process may provide the help that institutions require, streamlining the list of possible activities and groups.

In this section, we describe our proposal for dividing care-receivers into groups to perform activities every day during a period of time using a Coalition Structure Generation Problem. The criterion to generate coalitions relies on physical and psychological aspects of each care-receiver (i.e., preferences, health, friendship, etc.) and the profiles of activities (i.e., physical requirements and the number of people per activity).

The Coalition Structure Generation problem refers to partitioning the components of a set into exhaustive and disjoint coalitions optimizing certain criteria. In our problem, the components of the set are the care-receivers that take part in group activities proposed by a senior residence centre and the criterion to optimize is a social welfare function of each coalition (i.e., the degree of matching between the profile of the care-receivers and the activity in which they participate).

Definition 1. *Let $E = \{e_i, ..., e_n\}$ be a set of care-receivers where each individual has a set of features that describes his/her profile. Let $G_j \in E$ be a subset of E called group.*

The profile of each individual is defined by the following features:

- *Physical status* refers to the physical condition of the individual and can take three values based on his/her medical profile: independent, partially independent, or dependent. Depending on the physical status, there are some activities that are most suitable for an individual. The physical status is known from the beginning and usually remains almost constant during his/her stay in the centre.

- *Preference of activities* refers to how appealing is an activity for an individual. This feature can take three values: appealing, neutral, or non-appealing. We assume that an individual does not have any preference until he/she participates in an activity. Upon the activity completion the feedback is collected about his/her preference.
- *Friendship relationships* represents the social network of the senior residence centre. Nodes represent the individuals and links are weighted bidirectional relations between individuals that take three values: non-friends (i.e., the individuals consider each other annoying), neutral (i.e., the individuals are indifferent with each other), or friends (i.e., the individuals are friends). Initially, information of friendship is not available. After each activity, individuals provide information about his/her relationships with other activity members.
- *Historical activity* the profile stores the sequence of activities already performed by the individual during the planned period. This information is used to avoid the repetition of activities during an specific period of time. Individual preferences, friendship relationships and historical activity profile will be considered in future group activity configurations.

Definition 2. *Let $A = \{a_i, ..., a_n\}$ be a set of activities planned for a period of time (i.e., several weeks or months depending on the requirements of the senior residence centre). Each activity is defined by a set of features.*

The features associated to an activity are the *type* and the *number of participants*. The activities are classified as psychological or physical. Psychological activities include table games, artistic expression, reading, or religious events, among others. Physical activities include dancing, walks, gardening or culinary lessons, among others. The number of participants is set between a minimum and maximum number of individuals.

We define $< G_j, a_i >$ as a group of individuals that participate in an activity. Given a group $< G_j, a_i >$, the value associated to group is given by a characteristic function $v(< G_j, a_i >) : 2^E \rightarrow \mathbb{R}$ that assigns a real-valued payoff to $< G_j, a_i >$. The value of a group $v(< G_j, a_i >)$ is calculated as a linear combination of functions that calculate different types of matching. We define the following functions, whose values ranges from 0 to 1:

- Function $phy(e_j, a_i)$ calculates the degree of match between the physical features of an individual $e_j \in G_j$ and the physical requirements of the activity $a_i \in A$.
- Function $act(e_j, a_i)$ calculates the match between the personal preferences of each individual $e_j \in G_j$ and the activity $a_i \in A$ care-receivers.
- Function $fri(e_j, X)$ calculates the degree of friendship of an individual $e_j \in G_j$ with other members of the group $e_k \in G_j : j \neq k$ considering the social network X.

– Function $his(e_j, a_i, d)$ penalizes the group if an individual $e_j \in G_j$ has performed the activity $a_i \in A$ in the last d days.

Given the above functions, the value of a group is calculated as:

$$v(< G_j, a_i >) = \sum_{e_i \in G_j} \alpha \cdot phy(e_j, a_i) + \beta \cdot act(e_j, a_i) + \gamma \cdot fri(e_j, X) + \theta \cdot his(e_j, a_i) \tag{1}$$

Note that parameters α, β, γ, and θ are defined to give more relevance to specific features in order to build groups.

Definition 3. *A group structure* $S = \{< G_1, a_i >, < G_2, a_j >, ..., < G_k, a_n > \}$ *is a partition of groups such that* $\forall i, j(i \neq j), < G_j, a_n > \cap < G_i, a_k >= \emptyset$, $\bigcup_{\forall < G_j, a_n > \in S} < G_j, a_n >= E$.

The value of a group structure is denoted by $v(S)$, where $v(S)$ is an evaluation function for the group structure. In this work, we assume that the quality of each group is independent of other groups. Therefore, we can calculate the value of the group structure as:

$$v(S) = \sum_{< G_j, a_n > \in S} v(< G_j, a_n >) \tag{2}$$

The goal is to determine an optimal group structure for the organization of activities $\underset{S \in 2^E}{argmax}\ v(S)$.

It turns out that partitioning a set of elderly individuals into disjoint groups while optimizing a social welfare function corresponds to the formalization of coalition structure generation problems. In order to solve this problem, we propose the use of a genetic algorithm.

3 Genetic Algorithm Design

Genetic algorithms have been shown to be effective at finding approximate optimal solution, and, in some cases, optimal solutions to combinatorially explosive problems. To solve the coalition formation problem, we proposed a genetic algorithm (see Algorithm 1) that generates successive sets of solutions (generations), where each new generation inherits properties from the best solutions of the previous. Initially, the algorithm creates an initial random population of N individuals. Each individual is a solution to the problem (see Figure 1). Therefore, the size of the chromosome is the number of residents. The chromosome gene order corresponds to the different care-receivers, and gene values correspond to the activity number a care-receiver is engaged. More than one care-receivers engaged in the same activity constitute a coalition.

The *fitness function* evaluates the quality of the solutions (i.e., the quality of the individuals). The fitness function in our problem corresponds to function that

Care-receiver id	0	1	2	...			N
Activity id	14	7	7	...			10

Fig. 1. The encoding of a chromosome.

calculates the value of the group structure (see Equation 3). However, not all the fitness values of the individuals are calculated in the same way. In the described problem, there is a certain type of individuals that must be discarded for future generations, and therefore, they have a 0 fitness value. These individuals are those that are allocated to activities that exceed the maximum number of care-receivers or activities that do not reach the minimum required people.

$$v(S) = \begin{cases} \sum\limits_{G_j \in S} v(G_j) & \text{if } \forall G_j \in S : min\_size < |G_j| < max\_size \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Genetic operators are applied over the individuals. The algorithm considers four genetic operators (see Figure 2):

- Swap two different genes within an individual. This operator allows that two randomly selected participants from different activities swap his/her activities.
- Swap genes with a certain value for genes with another value within an individual. This operator allows to swap all participants of two activities selected randomly.
- Randomly replace genes with a certain value within an individual with a new, randomly chosen value. This operator allows to randomly change the activity of all the participants of a current coalition. This operator facilitate the inclusion of new activities.
- Swap genes with a certain value within an individual with genes with another value within another individual. This operator changes the activity of a group that is part of a planification with the activity of a group in other planification. This operator facilitate the inclusion of new activities.

The *genetic algorithm* is shown in Algorithm 1. A population consisting on a number of possible activities planifications is randomly generated. During each iteration (i.e., generation) of the algorithm, a randomly selected genetic operator is applied to each individual of the population and then, its fitness value is calculated according to Equation 3. Once the genetic operators are applied, the new individuals are inserted in the new generation. The best N individuals remain in the new generation and the others are removed. The process ends when at least one of these situations occur: (i) the number of generations is exceeded; (ii) when there are a certain number of generations where there is none individual in the new generation that has a higher value of fitness than

Algorithm 1 The Evolution Algorithm

Generate an initial population of N random individuals
Evaluate the fitness of each individual of the population N
Select the best solution s
Number of generations k = 0
Number of generations without improving the solution q = 0
Temporal constraint t = 0
while ($k < max\_gen \wedge q < max\_gen$ without improving) **do**
  for ($j = 0; j < N; j++$) **do**
    randomly apply one of the genetic operators over individual j
    evaluate the fitness value of j and j'
    insert j and j' in the new generation
  end for
  selection of N best individuals
  selection of the best individual s'
  if (s' $\leq$ s) **then**
    q++
  end if
  k++
end while

the best individual in previous generations; (iii) when the algorithm exceeds the time limit.

4 Experiments

In this section, we simulate five different scenarios in order to test the efficiency and performance of the algorithm proposed. For each scenario, we defined a population of individuals with different preferences in activities and friendship degree. We defined heterogeneous populations in which some individuals had a high friendship degree while others had a low friendship degree. Similarly, some activities were preferred by a high number of individuals while others were only preferred by few individuals. These five scenarios were configured as follows:

- *Scenario 1*: 43 individuals and 20 activities.
- *Scenario 2*: The 20 individuals with the highest degree of friendship and 20 activities.
- *Scenario 3*: The 20 individuals with the lowest degree of friendship and 20 activities.
- *Scenario 4*: 43 individuals and the 10 most preferred activities.
- *Scenario 5*: 43 individuals and the 10 few preferred activities.

In each scenario, groups of individuals were formed during 30 days in which the value of the group structure was calculated for each day, considering that each individual could carry out a single activity per day, and a penalization was introduced if the same activity was repeated in a three-days period. The

Example of operator 1

	0	1	2	3	4	...	39	40	41	42
ind 1	2	19	4	12	12	...	11	4	4	9

	0	1	2	3	4	...	39	40	41	42
ind 1'	2	19	11	12	12	...	4	4	4	9

Example of operator 2

	0	1	2	3	4	...	39	40	41	42
ind 1	2	19	4	12	12	...	11	4	4	9

	0	1	2	3	4	...	39	40	41	42
ind 1'	2	19	12	4	4	...	11	12	12	9

Example of operator 3

	0	1	2	3	4	...	39	40	41	42
ind 1	2	19	4	12	12	...	11	4	4	9

	0	1	2	3	4	...	39	40	41	42
ind 1'	2	19	16	12	12	...	11	16	16	9

Example of operator 4

	0	1	2	3	4	...	39	40	41	42
ind 1	2	19	4	12	12	...	11	4	4	9

	0	1	2	3	4	...	39	40	41	42
ind 1'	2	19	7	12	12	...	11	7	7	9

	0	1	2	3	4	...	39	40	41	42
ind 2	1	7	7	2	9	...	7	5	3	2

	0	1	2	3	4	...	39	40	41	42
ind 2'	1	4	4	2	9	...	4	5	3	2

Fig. 2. Examples of genetic operators.

size of each group ranged from 3 to 5 people per group. It must be pointed that some activities could be carried out by different group sizes while others must be only carried out by a specific number of group size. Note that an activity might have no individuals. the The value of each group is calculated considering that each factor (physical condition, preferences, friendship, and previous activities performed) of the fitness function has the same weight.

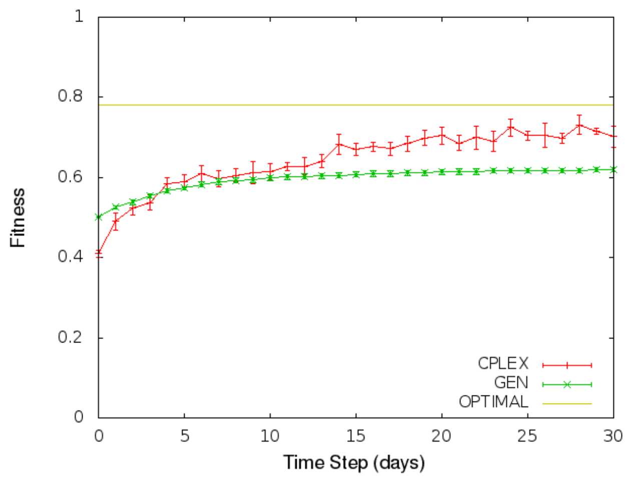

Fig. 3. Scenario 1.

In order to compare the efficiency of the genetic algorithm proposed, we also applied the commercial software *ILOG CPLEX 12.5* [3]. This software solves the problem as a linear programming problem [16] obtaining the best configuration for each day. In contrast, the computational time required to find the best configuration is expected to be high.

The execution of these two grouping strategies (*genetic algorithm* and *CPLEX*) was repeated 10 times for each scenario. Thus, each figure shows the 95% confidence interval, and Student's t-tests was performed to assess whether the differences among the strategies were significant. In addition, the upper bound of the highest value of the group structure is also represented as a continuous line above all the strategies. This upper bound represent an scenario in which all the preferences are known and any penalization is carried out.

[3] http://www.ibm.com/software/commerce/optimization/cplex-optimizer/ - Last access: 25/07/2016

4.1 Results

Figure 3 shows the results of the *Scenario 1*. As it can be observed in the figure, as the more information was considered for group formation, the higher the value of the group structure was.

Thus, both the *genetic algorithm* and *CPLEX* improved the performance during the 30 days, getting closer to the optimal. Although differences among both strategies were significant from day 15 on, the differences between the two strategies for all days that is lower than 0.1 in day 30, showing that the performance of the *genetic algorithm* algorithm is quite close to the *CPLEX*.

However, computational differences were notable. While the time required to obtain the optimal coalitional structure by the *genetic algorithm* was $14.21s \pm 0.41$, the time required by *CPLEX* was $689.56s \pm 47.78$.

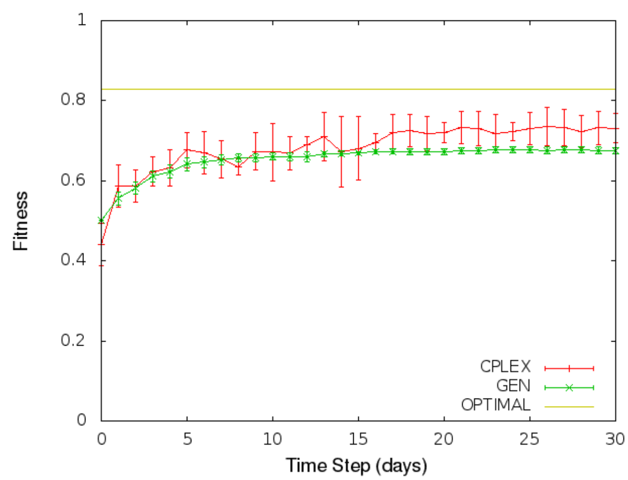

Fig. 4. Scenario 2.

In Figure 4 we can observe the results of the *Scenario 2*. Similar to the previous scenario, the performance of both strategies increased during the 30 days as more information was considered. In contrast, the differences between the *genetic algorithm* and *CPLEX* were reduced and the average values in the day 30 were lower than 0.06. Regarding computational time, since the population was lower than in *Scenario 1*, the time required by both strategies was also lower. Despite this, the *genetic algorithm* performance was much better, requiring $0.68s \pm 0.01$ to execute and iteration, while *CPLEX* required $3.76s \pm 0.12$.

Figure 5 shows the performance of *Scenario 3*, which was similar to the previous scenario. Since this correponds to a configuration in which individuals had a low degree of friendships, the values were low, and therefore, differences

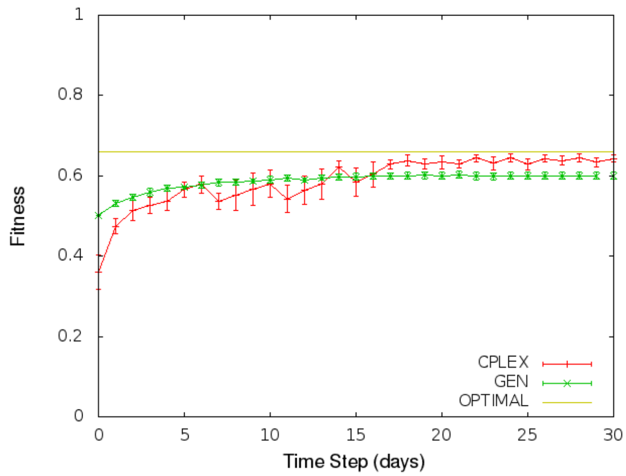

Fig. 5. Scenario 3.

between both strategies were also few. Although these were significant from day 17 on, the difference between the average values of the coalitional structure obtained in day 30 by the *genetic algorithm* and *CPLEX* were lower than 0.04. In this scenario, computational consumption was similar to the *Scenario 2*, being $0.72s \pm 0.02$ for the *genetic algorithm* and $3.84s \pm 0.18$ for *CPLEX*.

The next scenario, considered the same population that *Scenario 1* but the half of the activities. Similar to the previous scenarios, in *Scenario 4*, the performance of both strategies increased during the 30 days. In this case, since the values of the coalitional structure were high, differences between both strategies were higher than in other scenarios, becoming significant from day 16 on, becoming a difference of 0.06 between the average value of both strategies in day 30. Since the population was lower than in *Scenario 1*, the computational time required by the *genetic algorithm* was lower, being $1.74s \pm 0.05$. In contrast, this is not relevant for *CPLEX*, whose computational time was $692.10s \pm 34.60$

Finally, Figure 7 shows the performance of the *Scenario 5* for the *genetic algorithm* and *CPLEX*. This scenario is similar to the previous one but the activities considered were those preferred by the lowest number of individuals. This caused that the values of the coalitional structures were lower compared to *Scenario 4*. In this case, the differences between both strategies in day 30 were around 0.03. Computational times were similar to the previous scenario, being $1.92s \pm 0.06$ for the *genetic algorithm* and $686.80s \pm 31.82$ for the CPLEX.

As a general conclusion, it is observed that the performance of the *genetic algorithm* was quite close to the *CPLEX*, which obtains the coalitional structure with the highest value possible since all the possibilities are explored. However, the average time required for obtaining the solutions were considerably different, requiring much more time for *CPLEX* as we can observe in Table 4.1. In addi-

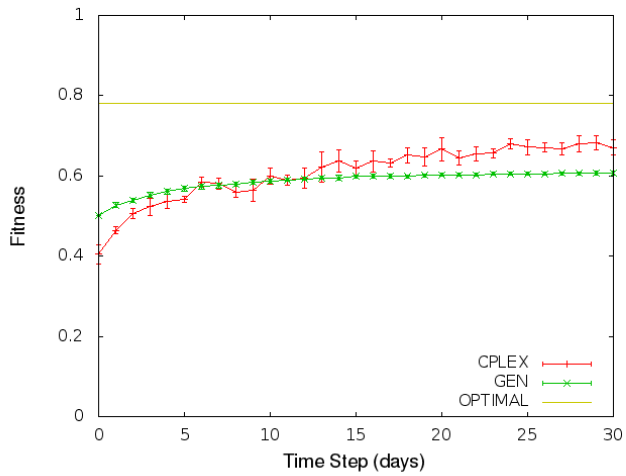

Fig. 6. Scenario 4.

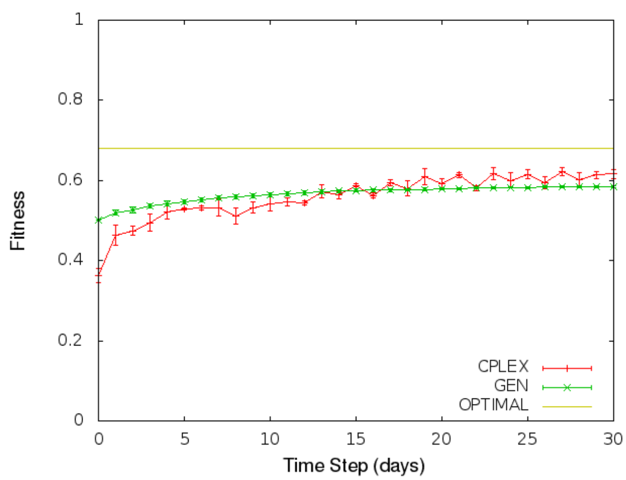

Fig. 7. Scenario 5.

Strategy	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Genetic algorithm	14.21 ± 0.41	0.68 ± 0.01	0.72 ± 0.02	1.74 ± 0.05	1.92 ± 0.06
CPLEX	689.56 ± 47.78	3.76 ± 0.12	3.84 ± 0.18	692.10 ± 34.60	686.80 ± 31.82

Table 1. Time consumption (in seconds).

tion, as it can be appreciated, as more complex scenarios are considered, more computational time is required, which would make some problems to become unmanageable at a reasonable time. In contrast, since the *genetic algorithm* provides quite optimal solutions in a response time much more lower, much complex problems could be managed.

5 Conclusions

In this paper, we presented a model for dividing care receivers into groups to perform activities with elderly people. This model allows the representation of physical requirements of the individuals but also preferences and social relationships. The model is also able to learn these features as activities are performed by care receivers and improves next activities configurations.

We represented the problem of finding the most suitable grouping as a Coalition Structure Generation problem, which we solved by implementing a Genetic Algorithm. The set of experiments presented demonstrated that the solution obtained by our algorithm was really close to the optimal values for all the scenarios proposed. What is more, the computational time required to find the solution was really small compared to the time required by *CPLEX*, which explores all the solutions. Therefore, our algorithm could be applied in more complex problems with large populations and activities.

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