# Agents in a Route Planning Application

P. De Causmaecker, P. Demeester, P. De Pauw-Waterschoot, G. Vanden Berghe

KaHo St.-Lieven,
Informatietechnologie,
Gebr. Desmetstraat 1,
9000 Gent, Belgium,
Tel: +32-9-2658610,
Fax: +32-9-2256269,
e-mail: {patdc,peterdm,phildp,greetvb}@kahosl.be

ABSTRACT

Characteristics of software agents, such as intelligence, autonomy, interactivity, and mobility, have motivated the investigation of applying agent technology to a real-world vehicle routing problem. This paper presents a new approach to successfully deploy agents in a mobile nursing service with time windows; using non-explicit information and discretely imitating human negotiation processes. While keeping the economic cost of the routes down, the system must take the personal requirements and wishes of the nurses into consideration. We demonstrate how the incorporation of reciprocal feelings amongst the personnel in agent like software components can lead to a higher quality global satisfaction. The agents introduced in this approach do not take part in the pure vehicle routing part of the problem; their role is restricted to representing the personnel and negotiating the assignment of trajectories on their behalf.

**Keywords:** software agents, agent negotiation, vehicle routing

# 1. Introduction

Intelligent agents have been advocated to allow for the building of more flexible and user-friendly systems [2,4,5,7,9]. In software they can, among other things, personally represent the human users and defend their interests. They can be configured manually or build on experience to negotiate with other agents or users. In this way, confidential and sensitive information about the user's availability, willingness, and feelings [3]... need not be published at system level to be useful. The agent can build a model of its user and of the system in which it is functioning. There is no need for an explicit model; it can be represented by hidden variables, only to be interpreted by the agent itself.

Many agent characteristics turn out to be extremely valuable for applications in the scheduling and timetabling domains. Especially when multiple objectives, like economic benefits and personal preferences are to be met. Agents are autonomous; they can make decisions on behalf of the person they stand proxy for. Agents can be mobile and travel over a network. Consider an example of a traffic jam that makes havoc of the timetable of a distribution firm. Instead of starting a telephone discussion with other possible drivers to solve this acute problem, agents can do the necessary negotiations and report the resulting route changes to the drivers involved. It is most interesting if the agents are intelligent enough to defend the interests of the people involved. In more advanced systems we can think of learning agents [8], constantly adjusting their behaviour by observing the person or system they represent. Not only, the calculation time for finding solutions will be reduced, but also the defence of personal interests can happen in a subjective way.

In this paper, we present an application of these ideas in a vehicle routing setting as an illustration of how agents can negotiate in a real situation. We thank Bart Aluwé[1] and Eva Lema[2] for putting forward this practical problem and for providing test data. Starting from a rather arbitrary solution of the vehicle routing problem, software agents deal with the assignment of the routes to the personnel. In this assignment, a number of subjective and private considerations are taken into account.
Section 2 describes the particular problem we address. The heuristics we used to generate the schedules are summarised in section 3. In section 4, we describe how negotiating agents can tackle the assignment problem. Section 5 summarises the entire approach by showing the sequence of the algorithms. Numerical results are evaluated in section 6. Finally, we conclude in section 7 and give some general remarks for future work.

# 2. The problem

We describe a route planning application, which was built to demonstrate the possibilities of an agent approach in situations where negotiations between users are necessary. The users are human and are more or less reluctant to communicate their personal wishes to colleagues. The personal preferences will not be part of the vehicle routing cost function; on the one hand because people want discreteness and on the other hand because it is very hard to express them in terms of cost parameters. Therefore this research will not stress on the vehicle routing part of the research but on the confidential and human aspects. The problem considered is the planning of a mobile nursing service. The nursing service owns a number of vehicles and it is manned by an equal number of

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[1] Bart Aluwé, Vrasenestraat 142, 9100 Sint-Niklaas, Belgium, Tel: +32-3-7779162
[2] Eva Lema, Groenestraat 42, 8755 Ruiselede, Belgium, Tel: +32-51-689168

nurses. The problem involves a number of patients with time windows and different geographical data. In this approach, also nurses' addresses are dealt with.

Nursing personnel will visit patients at home, according to a trajectory that is only released the evening before. The application should take into account travelling times and time windows. It should also support the assignment of the trajectories to the travelling nurses.
The requirements naturally split into two sets, one for finding the trajectories, and one for the assignment of these trajectories to individual persons. The trajectories should be optimised with respect to economical criteria, patient satisfaction, and quality of service. The assignment process is mainly guided by limitations in the availability of the nursing personnel, its working conditions, and its degree of job satisfaction. The trajectory requirements turn out to be the easiest to quantify and can be measured on a daily basis. Items as working conditions and job satisfaction, on the other hand, are of a subjective nature. They ask for a more subtle approach, must take into account confidential data, and must be optimised over a longer period than one day. Especially when a personnel member does a good office to a colleague, this will be remembered and often rewarded by granting a future request of the person.
The combined 'vehicle routing – personnel satisfaction' problem arises in various domains like delivery and courier services, public transport and freight traffic. Thus, the problem is interesting not only from the theoretical but also from the practical point of view. Applications become especially interesting once real-time rescheduling is necessary. We can easily imagine several reasons why a schedule cannot be respected e.g. traffic jams or having a breakdown. A quick recalculation of the trajectories, combined with an intelligent assignment to the personnel is very useful, especially if the personnel can trust their agents to look after their interests in the negotiation process.

## 2.1. Trajectories

All trajectories constructed to visit the patients start and end in the central depot. We consider the following requirements for the routes:

- **Economy**: The number of nurses and their travelling time must be as low as possible in order to restrict the fleet of cars and personnel costs to a minimum.
- **Time windows**: Depending on the care required, some patients can only be visited within certain time windows. An insulin patient, e.g., must be injected before breakfast. For other treatments, the exact time is not so important. Cleansing a wound, for example, can happen at any time during the day. Patients can, for personal reasons, specify rather broad time windows such as before or after lunchtime.
- **Working hours**: Each nurse should work approximately 8 hours a day. The algorithm will map out trajectories of preferably 8 hours.
- **Starting point**: The trajectories start and end in a central depot. Nurses collect their material and medicines in the morning and bring their equipment back after finishing their job responsibilities.

## 2.2. Personnel

Adjusting personnel constraints is a private matter for the individual nurses. The solutions have to satisfy the following set of requirements of which the data are entered confidentially.

- **Starting time, finishing time, overtime:** Nurses have their own reluctance or eagerness to start earlier than other nurses do, or to work longer than the prescribed 8 hours. The assignment of the routes to the persons should consider these confidential data.
- **Lunch at home:** The personnel often prefer to have lunch at home. In the case where some nurses and patients live in the same neighbourhood, we want the last patient scheduled in the morning to be one who lives near the nurse's home.

- **Fairness:** The nurses should be treated equally. Considering the fact that constraints cannot always be satisfied in real world applications, we avoid assignments to be systematically worse for one member of the team than for the others.

Although the trajectory constraints and the personnel constraints are interdependent (e.g. the 8 hours limitation is weakened by the willingness to work in overtime), we decided to treat the two sets separately. The trajectory restrictions are very general constraints while satisfying the personnel constraints is a little bit more flexible.
We deliberately did not put personal preferences in the vehicle routing cost function. Instead of adding the personnel's address to the patients' data and consider the preferred lunchtime as a time window constraints; the preferences can remain secret for other personnel. It is the aim of this research to come close to human behaviour, which is too imprecise to put in a numerical cost function (e.g. one good turn deserves another; people will not spread about that they do not mind weekend work from time to time because this would incite everybody else to avoid weekends).
These considerations led to an approach in which the first set of restrictions is made explicit (section 3) before any calculation with respect to personnel constraints, starts (section 4). The solution of the trajectory constraints will not be altered at any later stage in the algorithm.

# 3. Generating the Trajectories

The requirements of subsection 2.1 define a vehicle routing problem with time windows. Solving this problem is conducted in two phases. In phase 1, we implemented a savings algorithm based on the classical Clarke and Wright approach to produce a first approximation [1]. A Tabu Search algorithm further refines this solution in order to produce a reasonably improved set of trajectories in phase 2. Compared to other algorithms described in literature [6] the algorithm described in this paper is very basic. For two reasons we did not develop or use more sophisticated algorithms:

- The aim of this research is to demonstrate the benefits of agent technology in routing problems instead of competing with other vehicle routing algorithms [10,11]. More specifically, agents will defend private (hidden) personnel objectives that are not to be measured in the same quantities as the economic criteria of the pure route planning. Unlike in Fischer [2], the agents presented in this paper are modelled such that they come close to interactions among humans.
- Since the agents' task only starts after the trajectories have been calculated, an excellent solution from the economic point of view will not necessarily lead to a higher personnel satisfaction. The personal preferences and the vehicle routing objectives are incommensurable anyway.

The routing part Phase 1 is presented in Fig. 1. The figure demonstrates that the time window constraint is explicitly checked.

1. Calculate savings: determine for each pair of patients the difference between visiting both patients separately, returning to the depot in between, and visiting one patient after the other and then returning to the depot at the end.
2. Put the savings in a sorted list.
3. Select the largest saving from the list.
4. If both patients are still connected to the depot and if both patients are not yet together in one loop and if the time window constraints are satisfied, add the connection by joining two loops into one.
5. If all savings from the list have been investigated then stop; else go to step 3.

**Fig. 1** Phase 1: Savings algorithm with time windows

To simplify the matter of meeting the time window constraints, we defined a symmetric driving time between two patients. If, for example, a patient has a very narrow time window, the possibility to traverse the trajectory in two directions multiplies the probability for matching this constraint by two. Thus, while building the routes, the algorithm keeps the two traversal directions open. Additional degrees of freedom are the starting hours of the nurses, and the possibility to introduce waiting time between two visits. In the experiments, this approach turned out to generate sufficient flexibility to generate feasible sets of trajectories. Quite often however, these sets were far from satisfying. Too many nurses were required, and the travelling times often showed, by simple visual inspection, longer than necessary. Part of the problem originated in the very strict application of the time windows.

Another cause of error is the sub optimality of the savings algorithm itself. These two defects turned out to amplify each other in this application, so that the results were not a sufficiently good starting point for our negotiating agents. Several authors (see e.g. [6]) report on the successful use of meta heuristics to improve on the initial results, Tabu Search being one of the better possible choices. We thus decided to implement a Tabu Search algorithm in phase 2. The Tabu Search algorithm is schematically explained in Fig. 2. The step or move in the Tabu Search algorithm is a displacement of a patient from his current position in the route to a position just after or before a neighbouring patient. After insertion, the driving times are optimised with the altered route and finally the route is re-evaluated. The neighbourhood is determined as the set of the PERC percent nearest patients, PERC being a modifiable parameter of the algorithm. After a predefined number of iterations without improvement, the algorithm stops. We use no diversification scheme, apart from the tabu list. The attributes of a move stored in the tabu list are such that a patient X who has been removed from between patients Y and Z cannot be placed next to Y or Z for the next 'list size' iterations. The only parameters for the algorithm, the tabu list length and the stop criterion, have been experimentally determined but they are adjustable by the users. Imitating manual planners, who will not combine patients who live very far from each other will not be combined in the same routes in the first instance, we have experimented with several values for PERC as well. The test results presented in section 6 are obtained with PERC=60 (when considering moves in the Tabu Search algorithm, we only consider the 60% nearest neighbours for every patient). The tabu list length is 17 and the stop criterion in these experiments is set to 500 iterations without improvement. The value of the cost function is the sum of the penalties for each of the constraints. The distance between patients in our demonstration problem is measured as the straight line between their locations, which co-ordinates are given in km. We choose a penalty of 1 for the total driving time of a solution, with a constant driving speed of 60 km/h. Not respecting the working time of 8 hours generated a penalty per minute both for shifts that are too short and shifts that are too long. Arriving early or late in a patient's house generates a penalty proportional to the earliness or lateness (in minutes) and to the weight factor. The weight factors for earliness and lateness are not necessarily equal and they are modifiable per patient.

1. Calculate the PERC % closest neighbours for every patient.
2. Save the Clarke & Wright result as the best solution.
3. While the stop criterion (number of iterations without improvement) is not reached
4. Calculate the value of the cost function for every possible swap of two neighbouring patients.
5. Perform the best move allowed. A move is allowed when it is not forbidden by the tabu list or when it provides a better solution than the best one found so far.
6. If the current solution is better than the best, replace the best solution.
7. Update the tabu list and continue from step 3.

**Fig. 2** Phase 2: Tabu Search algorithm to improve the Clarke & Wright result.

# 4. Assigning the Trajectories

The combination of a savings algorithm with Tabu Search delivers an economically improved set of routes. The next step in the algorithm organises the assignment of routes to the individual nurses. For maximal personnel satisfaction, it is important that the nurses can specify their very diverse points of interest. High flexibility and confidentiality are of extreme importance.

To realise a high quality assignment of the routes, we based our architecture on the agents' metaphor. Our agents are software components, each of which is dedicated to a member of the personnel. Every agent carries its master's profile and preferences, as well as some memory of how well it could co-operate with other agents in the past. The agents will support the assignment process through negotiation.

The individual trajectory cost is the driving force for the negotiations. The agents typically pass this cost to the system, without detailed information about how it was calculated. The denotation of this cost is explained in subsection 4.1.

Using the individual loop costs (trajectory costs); the system drafts a first assignment. This assignment algorithm is explained in subsection 4.2.

At this stage, the agents can start discussing the draft assignment. The negotiation process is used here to try to optimise personnel satisfaction. A detailed description of this approach can be found in subsection 4.3.

## 4.1. Individual Costs

In this research, we allowed the nurses to adjust their preferences for three criteria. The parameters for these criteria are used in the personal cost functions for trajectories.

- **Starting time**: A nurse can prefer to start at 7 in the morning, while another one may be very reluctant to start later than 6.
- **Overtime**: Some nurses like to work in overtime, while others try to stick to the regular working hours.
- **Lunch break**: The normal duration of a lunch break is two hours. Many nurses like to take their lunch at home and they prefer routes in which they are not far away from home around lunchtime.

In the "agent configuration" process, each nurse assigns a weight to each of the criteria. The weights will determine the intentions of the agents while negotiating. With these weights, the trajectory cost for the nurse can be calculated.

Nurses cannot see each other's agents, and the agents will never communicate their configuration settings directly.

## 4.2. Draft Assignment

To initiate the discussion, the system generates a first assignment of the trajectories to the nurses. This draft will be the starting point for the negotiation process to be discussed in the subsection 4.3. It starts with an inquiry of all the agents. They generate a cost for each of the routes. Consequently, a matrix with individual costs is obtained. The system then quite arbitrarily assigns routes to nurses so that the result is reasonably good. It goes linearly through the list of routes selecting the nurse with the lowest individual cost of those who have not been assigned a trajectory yet. Although an optimal assignment (from the central planner's economical point of view) could easily be generated, our rather ad hoc assignment turned out to be a good starting point for the negotiation process that follows.

In case the number of trajectories is lower than the number of personnel available, the algorithm works with a subset of the number of nurses. Only the agents of the nurses who will work that day contribute to the negotiations in our algorithms. A more advanced approach could possibly allow all the agents to take part in the discussion.

## 4.3. Negotiation

The assigned route determines the satisfaction of the nurse, which is defined by the value of the personal cost function. Experiments with different values of the satisfaction level showed 30 to be close to what we intuitively consider satisfactory for most people. Users are free to adjust this value if required. A route cost (further called loop cost) below 30 indicates satisfaction, while a cost over 30 identifies an unsatisfactory situation.

In the negotiation phase, agents start switching between three possible states: enquiring, listening, and occupied. An agent with a satisfactory trajectory enters the listening state, while an unsatisfactory route will lead him to the enquiring state. Agents in the enquiring state will search the set of routes for more interesting candidates, according to their personal cost function. They select the most interesting candidate from this list that is in the listening state. Upon the start of the negotiation, which follows, the selected agents enter the occupied state.

We will now describe the conversation between an enquiring agent E and a listening agent L. E proposes to exchange loops (trajectories) and L calculates a cost for the exchange.

The cost is composed as follows:

- the augmentation of his personal loop cost (may be negotiated).
- the sympathy L feels for agent E. This sympathy is expressed as a number and will be influenced by previous exchanges involving agent E. Mathematically it is expressed as:

$$\text{cost} = \text{Loopcost} - \frac{\text{Sympathy}}{2} \tag{1}$$

The numbers have been normalised such that the cost can always be evaluated against a [0,80] scale. Users are free to adapt this interval to their own preferences but for our experiments 80 proved to be satisfactory. A cost less than zero will be accepted; a cost over 80 is rejected. Between these limits, the probability of acceptation is equal to

$$1 - \frac{\text{cost}}{81} \tag{2}$$

If agent L rejects, he mentions this to E who will search for another candidate. In the case of acceptation L sends his loop cost to E. If E accepts, he will augment his sympathy for L by this loop cost, while L will lower his sympathy for E by the same value. Acceptation of the offer by L is determined as follows:

- a cost lower than 20 is always accepted (20 is determined after comparative experiments and comes close to real world negotiations)
- between 20 and 80, the probability of acceptance is:

$$1 - \frac{\text{cost} - 19}{61} \tag{3}$$

Upon acceptance, trajectories are exchanged, sympathy values are adjusted, agents E and L determine their new states, and the negotiation process continues. The negotiation ends

- when all agents are in the listening state
- when no agent in the enquiring state finds a potential exchange partner.

# 5. Algorithm

Figure 3 gives an overview of the heuristics sequence described in the sections 3 and 4. It is clear that the algorithm divides in two more or less independent phases. In our approach we choose not to let agents contribute to the pure vehicle routing step, their role starts from the assignment part of the method.
After the calculations and negotiations, the result is presented as a set of trajectories assigned to nurses. Possible route swaps among nurses will only affect the 'sympathy' levels of the corresponding agents. These results belong to the confidential part of the program and are not communicated to the users.

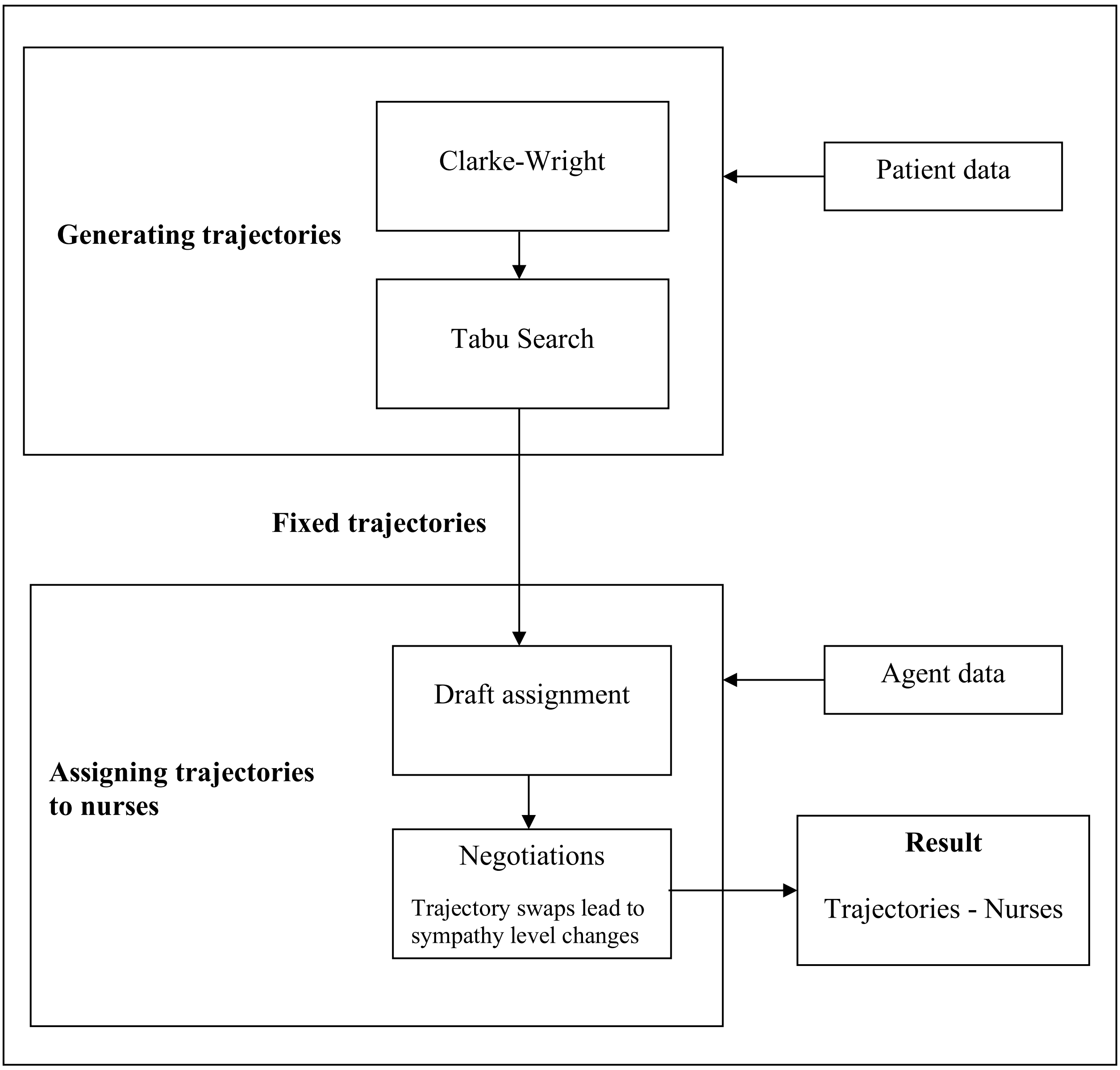


**Fig. 3** Diagram of the algorithms used to solve the mobile nursing service problem

## 6. Results

To demonstrate the mechanisms of this approach, the algorithms are tested on two sets of data, similar to real world situations. Geographical locations are represented by their co-ordinates and we always suppose a sufficient number of personnel members available. We provide test sets on http://project.kahosl.be/coala/sympathetic_agents.htm. The results are presented in Tables 1 till 5. The example P60 consists of 5 nurses and about 60 patients to visit daily. In the P140 example, there are more or less 140 patients per day and 12 available nurses. In both examples, the number of patients and their requirements somewhat fluctuate in time. We choose 7 slightly different patients sets, corresponding to the 7 days of a week. We have run the program for seven consecutive days, to demonstrate the influence of negotiations and sympathy changes on the results.

In Table 1, the improvements of the tabu search algorithm on the results of the savings algorithm are presented for 7 data sets (7 days of the week). We have copied both data sets to the subsequent weeks for testing. Since the main goal of this research was to show the advantages of agent technology for scheduling problems, we have not concentrated on developing a very powerful tabu search algorithm. The reduction in the total cost of the schedules, however, is considerable: on average, the algorithm achieved an improvement of 18% in the P60 example and 20% in the P140 example. Applying the tabu search step after the savings algorithm will thus benefit the organisation taking fuel and fleet of cars into account. It is only in the next phase that we will concentrate on personnel constraints and preferences.

| **P60** | **Savings Algorithm** | **Tabu Search Algorithm** | **Cost reduction (%)** |
|---|---:|---:|---:|
| **Monday** | 103878 | 82385 | 21 |
| **Tuesday** | 106162 | 83243 | 22 |
| **Wednesday** | 83854 | 81328 | 3 |
| **Thursday** | 85004 | 76374 | 10 |
| **Friday** | 103878 | 82385 | 21 |
| **Saturday** | 106162 | 83243 | 22 |
| **Sunday** | 104283 | 77318 | 26 |

| **P140** | **Savings Algorithm** | **Tabu Search Algorithm** | **Cost reduction (%)** |
|---|---:|---:|---:|
| **Monday** | 241608 | 201184 | 17 |
| **Tuesday** | 265842 | 233861 | 12 |
| **Wednesday** | 297475 | 203421 | 32 |
| **Thursday** | 261758 | 216190 | 17 |
| **Friday** | 264413 | 211036 | 20 |
| **Saturday** | 261995 | 187870 | 28 |
| **Sunday** | 224696 | 195056 | 13 |

**Table 1** Comparison of the cost function before (only the Savings Algorithm) and after the Tabu Search Algorithm was applied

The test results of the agents' negotiations are presented in Tables 2 and 3. We have run the algorithm on the data sets of 7 consecutive days, taking different data for each day of the week. Only for demonstrating the impact of the negotiations and exchanges on the sympathy levels of the nurses, the nurses are every day the same ones. In the Table 2, the sympathy values are shown after the negotiations on the results of the assignments of the tours. As we can see, there is not one nurse who escaped from actively participating to the negotiations; they have all changed their sympathy towards at least one nurse.

| **P60** | **Nurse A** | **Nurse B** | **Nurse C** | **Nurse D** | **Nurse E** |
|---|---|---|---|---|---|
| **Nurse A** | 0 | 2 | 22 | 13 | 0 |
| **Nurse B** | -2 | 0 | -6 | 32 | 20 |
| **Nurse C** | -22 | 6 | 0 | 48 | 0 |
| **Nurse D** | -35 | -32 | -48 | 0 | -43 |
| **Nurse E** | 0 | -20 | 0 | 43 | 0 |

**Table 2** Sympathy level (of the nurses in the columns for the nurses in the rows) in example P60 after the negotiations.

| | **P60** | | **P140** | |
|---|---|---|---|---|
| | Number of swaps | Sympathy transfer | Number of swaps | Sympathy transfer |
| **Monday** | 0 | 0 | 4 | 112 |
| **Tuesday** | 4 | 86 | 2 | 38 |
| **Wednesday** | 0 | 0 | 0 | 0 |
| **Thursday** | 2 | 62 | 0 | 0 |
| **Friday** | 0 | 0 | 8 | 190 |
| **Saturday** | 4 | 82 | 2 | 38 |
| **Sunday** | 0 | 0 | 2 | 82 |

**Table 3** Number of negotiations leading to a swap in trajectories and sympathy transfer per test day for the problems P60 and P140.

Table 4 presents the results of the assignment algorithm (bold figures) and shows the result of the agents' negotiations (italic figures) for the problem P60. It is obvious from the figures that the most satisfactory schedule for the agents does not necessarily correspond to the economic optimum. This is the case in the 'Monday' example for the problem P140 (see Table 5): the value of the cost function has increased after the negotiations. If we trace the negotiations, we can see that agent C first proposes agent B to swap routes. Since B is not interested in this swap, agent C continues his search and obtains a positive answer from A. After that, A is no longer entirely satisfied and he starts a successful negotiation with E. Although the overall result of this last action seems negative (A: 70->102 and E: 46->46) the mechanism of sympathy renders a higher number of satisfied agents.

| **Monday** | **Route 1** | **Route 2** | **Route 3** | **Route 4** | **Route 5** |
|---|---|---|---|---|---|
| **Nurse A** | 49 | 49 | ***12*** | 45 | 82 |
| **Nurse B** | ***0*** | 60 | 30 | 30 | 30 |
| **Nurse C** | 6 | 34 | 48 | 33 | ***23*** |
| **Nurse D** | 7 | ***16*** | 20 | 16 | 22 |
| **Nurse E** | 10 | 23 | 29 | ***23*** | 25 |

| **Tuesday** | **Route 1** | **Route 2** | **Route 3** | **Route 4** | **Route 5** |
|---|---|---|---|---|---|
| **Nurse A** | 44 | 35 | 65 | ***13*** | 70 |
| **Nurse B** | *60* | 40 | 40 | 40 | **70** |
| **Nurse C** | 68 | ***15*** | 7 | 42 | 35 |
| **Nurse D** | **34** | 4 | *12* | 16 | 24 |
| **Nurse E** | 53 | 17 | **19** | 19 | *40* |

**Table 4** Personal cost function values for the trajectories (Route 1-5) on the first and second day of the test period for P60. The bold figures show the routes that are assigned to the

people before the negotiations start. The italic figures are the results after the negotiations.

| **Monday** | **R 1** | **R 2** | **R 3** | **R 4** | **R 5** | **R 6** | **R 7** | **R 8** |
|---|---|---|---|---|---|---|---|---|
| **Nurse A** | 63 | 68 | 24 | *46* | 134 | **69** | 100 | 70 |
| **Nurse B** | ***0*** | 110 | 110 | 110 | 120 | 120 | 90 | 100 |
| **Nurse C** | 53 | 87 | 45 | 64 | 220 | *84* | 125 | **77** |
| **Nurse D** | 29 | ***66*** | 30 | 41 | 156 | 60 | 84 | 55 |
| **Nurse E** | 24 | 127 | 34 | **46** | 280 | 88 | 142 | *102* |
| **Nurse F** | 31 | 85 | 48 | 69 | 160 | 98 | ***96*** | 90 |
| **Nurse G** | 44 | 85 | 70 | 79 | ***116*** | 87 | 98 | 80 |
| **Nurse H** | 30 | 160 | ***0*** | 10 | 400 | 70 | 190 | 110 |

| **Tuesday** | **R 1** | **R 2** | **R 3** | **R 4** | **R 5** | **R 6** | **R 7** | **R 8** | **R 9** | **R10** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Nurse A** | 97 | *20* | 24 | 42 | 83 | 58 | 67 | **44** | 63 | 60 |
| **Nurse B** | **0** | 0 | 0 | 80 | 80 | 80 | 70 | 100 | *30* | 30 |
| **Nurse C** | 105 | 42 | 49 | 11 | 34 | ***23*** | 81 | 59 | 28 | 49 |
| **Nurse D** | 72 | 17 | 21 | *7* | 26 | 16 | 49 | 35 | 25 | 33 |
| **Nurse E** | 122 | 9 | 15 | 25 | ***27*** | 21 | 74 | 38 | 24 | 28 |
| **Nurse F** | 87 | 17 | 35 | 45 | 57 | 41 | ***54*** | 65 | 59 | 66 |
| **Nurse G** | 51 | 19 | *15* | 65 | 95 | 80 | 77 | 74 | **46** | 42 |
| **Nurse H** | 180 | **0** | 0 | 0 | 0 | 0 | 90 | *0* | 0 | 0 |
| **Nurse I** | 126 | 0 | **0** | 24 | 24 | 24 | 84 | 30 | 9 | *9* |
| **Nurse J** | *20* | 53 | 56 | 60 | 88 | 77 | 86 | 115 | 36 | **61** |

**Table 5** Personal cost function values for the trajectories (Route 1-8 for the 'Monday' problem and Route 1-10 for the 'Tuesday' problem) on the first and second day of the test period for P140. The bold figures show the routes that are assigned to the people before the negotiations start. The italic figures are the results after the negotiations.

## 7. Conclusions

Combining a simple vehicle routing heuristic with tabu search provides us with satisfying solutions both from the economical and human point of view. By realising a negotiation scheme to assist in the assignment phase, we achieved very encouraging results allowing re-assignments of some trajectories. The incorporation of sympathy in the system guarantees long term fairness of the planning system. It comes very close to real world negotiation processes among personnel members. Experiments with sets of up to 140 patients and 10 nurses indicate that the system produces assignments with a significantly higher overall personnel satisfaction. The results demonstrate clearly how agents negotiate on the results of the assignment algorithm and very often agree on changes that are not necessarily more economic. Thanks to the mechanism of sympathy, we can see that there is no overall preferential treatment of any person.
Since the proposed approach fulfils the expectations, it will be very interesting to implement our system in a real world mobile nursing environment. This will enable us to further fine-tune the adjustment of the preference parameters
It will also be very interesting to investigate how the responsibility of the agents can be expanded. Agents could, for example, be in a position to negotiate on changes in the routes.
The results of this work tempt us to also apply the method to other scheduling and timetabling fields that can benefit from agent representatives for resources. Interesting applications are job shop

scheduling (in which agents can act for orders, machines…), university and exam timetabling (teachers, students…), stock cutting, and of course various other vehicle routing applications.

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