

Decentralized resource allocation for road passenger transportation*

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Abstract. Inter-urban road passenger transportation requires the allocation of drivers and buses to transport people. In such allocation process, several constraints on driving time are being imposed by the governments in order to assure citizens safety. Such constraints, however, are posing a lot of difficulties to the allocation process, usually generated by human operators. In this paper we formalize the problem and provide an auction framework based on a multi-agent environment in order to give a first approach to the problem solution. Such framework is decentralized because each agent computes the utility of its bids regarding private information that is not explicitly known by the decision maker. Particularly, we propose the use of combinatorial auctions. The first results obtained in the first prototype developed are provided and discussed.

1 Introduction

Transportation problems are a matter of concern from the Artificial Intelligent research community, and particularly, from the Planning and Scheduling community, as the recent publication of [1] has shown. However, most of the problems are related to logistics for industrial procurement [2], traffic control [3], and even bus routes for cities [4]. However, the inter-urban transport poses particular challenges to the research community that have not been tackled before. The definition of different time measures, as effective working time, presence time, break and weekly break time, characterize the problem with quite complex constraints and preferences not handled in other domains. The challenge is not so much related to regular and down town services that can be scheduled once a year, but to just-in-time services. That is, services required within a short period of time, usually, from one day to the next one. This kind of services are often related to conference events, holidays, excursions, etc., which are provided by inter-urban transport companies.

In the past, human operators in the inter-urban transport companies were in charge of allocating drivers to required services once a day. For example, at night, when all the customers have already performed they requests, the operator dedicate so much time to the allocation process. New laws and regulations,

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however, are posing too many constraints for being manually managed. As a bypass solution, operators elaborate schedulers in which drivers have unoccupied hours. The economic consequences for the benefits of the companies are evident: with the same amount of drivers, they can provide less services, and so they earn less money. Moreover, there is no guarantee that all the constraints imposed by the law are satisfied, so the company is assuming the risk to be billed by the traffic authorities.

Trying to allocate buses and drivers to services, is a well known allocation problem. Particularly, after observing that most of the constraints are related to the resources (drivers), we think that we are tackling with a decentralized allocation model, in which each resource (driver) is locally controlling its constraints. There are two main research lines regarding decentralized allocation problems: distributed constraint optimization problems [5] and multi-agent resource allocation [6]. Based on our previous experiences [7, 8], we model the problem as a multi-agent resource allocation, and particularly, by following an auction approach as explained in this paper.

This paper is organized as follows. First, we give a description of the road passenger problem in section 2. We continue by giving our approach to solve the problem in a decentralized environment in section 3, and particularly the auction framework in section 4. We proceed by giving our first results in section 5 and we end with some discussion and conclusions in 6.

2 Problem description

In the road passenger transportation domain we are given with two set of resources, drivers $D = \{d_1, \dots, d_n\}$ and buses: $B = \{b_1, \dots, b_m\}$, and a set of tasks (services) to be performed by using the resources $S = \{s_1, \dots, s_l\}$. The problem consists on assigning to each service a driver and a bus, subject to the constraints and preferences provided by the government. Since each driver has a bus assigned by default, with some exceptions, we ignore buses in a first approximation to the problem.

The time unit used in the allocation process is the hour. However, in order to verify the different constraints imposed by law, the definition of a *sliding time window* of one month is also required. For convenience, we consider a month composed by 28 days organized in four weeks: week 1 (from day 1 to 7), week 2 (from day 8 to 14), week 3 (from day 22 to 28) and week 4 (from day 22 to 28). All the definitions that follows are contextualized within this sliding time window.

2.1 Services

Definition 1. A *service* is a tuple

$$s_i = \langle ti_i, tf_i, dur_i, orig_i, dest_i, n_i, D^i, b_i \rangle$$

where ti_i is the initial time, tf_i the final time ($tf_i > ti_i$), dur_i the service duration, $orig_i$ the place where the service starts, $dest_i$ the destination place, n_i the number of passengers, D^i the drivers assigned ($D^i = \{d_1^i, \dots, d_{p_i}^i\}$ and $|D^i| \geq 1$) and bi the bus allocated.

2.2 Drivers

Definition 2. A *driver* is a tuple

$$d_i = \langle \mathcal{T}_i^d, \mathcal{T}_i^p, \mathcal{T}_i^b, \mathcal{T}_i^w, p_i, pkm_i \rangle$$

where \mathcal{T}_i^d , \mathcal{T}_i^p , \mathcal{T}_i^b , and \mathcal{T}_i^w are four different time measures (effective working time, presence time, break time and weekly-break time, see below), p_i is the basic cost and pkm_i is the cost per kilometer.

The *effective working time* \mathcal{T}_i^d measures the time the driver i is effectively driving a bus. This time includes auxiliary works.

Definition 3. The *effective working time* \mathcal{T}_i^d for driver i is defined as the set of all dairy effective working times within the sliding time window:

$$\mathcal{T}_i^d = \{T_i^{d_1}, \dots, T_i^{d_{28}}\}$$

where: $T_i^{d_j}$ is the dairy effective working time for day j .

The *dairy effective working time for day j* , $T_i^{d_j}$, is the sequence of all time slots assigned to driver i for driving a bus along journey j .

The *presence time* \mathcal{T}_i^p measures the time the driver is in the bus but not driving.

Definition 4. The *presence time* \mathcal{T}_i^p for driver i is defined as the set of all dairy presence times within the sliding time window:

$$\mathcal{T}_i^p = \{T_i^{p_1}, \dots, T_i^{p_{28}}\}$$

where $T_i^{p_j}$ is the dairy presence time in day j .

The *dairy presence time for day j* , $T_i^{p_j}$, is the sequence of all time slots assigned to driver i along journey j in which he/she is not driving. There should be a relationship between two consecutive effective working time slots, t_i^d and t_{i+1}^d and a presence time slot in between, t_j^p . That is, if two consecutive effective time slots have some time gap, such time gap should correspond to a presence time slot.

The *break time* \mathcal{T}_i^b measures the time the driver is out of the vehicle along its journey. The minimum length is one hour.

Definition 5. The *break time* \mathcal{T}_i^b for driver i is defined as the set of all dairy break times within one month:

$$\mathcal{T}_i^b = \{T_i^{b_1}, \dots, T_i^{b_{28}}\}$$

where $T_i^{b_j}$ is the dairy break time for day j .

The *dairy break time for day j* , $T_i^{b_j}$, is the sequence of all time slots assigned to driver i along journey j in which he/she is out of the car.

The *weekly break time* \mathcal{T}_i^w measures the time the driver has continuous break along a week (week ends, holiday). Weekly break time includes dairy break time. Both concepts, break and weekly-break should be considered as separated entities related to constraints required by the UE.

Definition 6. The *weekly break time* \mathcal{T}_i^b for driver i is defined as the set of all four break times corresponding to the four weeks within the sliding time window:

$$\mathcal{T}_i^w = \{T_i^{w_1}, \dots, T_i^{w_4}\}$$

where $T_i^{w_j}$ weekly break time in week j

The *weekly break time for week j* , $T_i^{w_j}$, is the sequence of all time slots assigned to driver i along week j in which he/she is either out of the office.

2.3 Constraints and preferences

The following hard constraints should be satisfied in any allocation solution:

Coverage The addition of all the time slots of effective working time of the drivers allocated to a service should cover the duration of the service.

Overlapping Different services with common drivers assigned should not have overlapping times.

Constraints on journey The maximum time a driver can be at work within a day is 12h.

Constraints on effective working time There are several maxima on the effective working time: 9 hours in a day (exception: 10h twice a week.), 90 hours in a week, and 4.5 h of continuous driving time. Violation of any constraint up to 20% of the time, is considered a minor fault.

Constraints on presence time : the maximum is 20h per week in average in a month period.

Constraints on break time : the minimum continuous break time between two consecutive journeys is 11h (exception: 9h three times a week). In case that the time is split in several bits at least one of the bits should be 8h long, the remaining bits should be at least 1h long, and the total amount of all the bits should be 12h. Vehicles with two drivers are allowed to have a minimum continuous break time of 8h within 30hours.

Constraints on weekly break time : the minimum continuous weekly break time at home is 36 hours, out of home is 24 hours. The recommended (normal) time is 45 hours. If this time is less than 45 hours, the differential should be recovered in the next three weeks

It is important to note that exceptions allows some scheduling flexibility that can be taken into account in the allocation process. For the sake of length, we do not include the formal specifications of the constraints and preferences here (see [9] for a full description and formalization of the problem).

Regarding preferences (soft constraints), they are defined in two layers:

Global These preferences are related to the business rules. They are:

Cost Drivers with low cost are preferred than expensive drivers. Low cost drivers means 0 basic cost, since they are employer of the company. Otherwise, drivers are hired as required.

Continuity Time slots of effective working time for a given driver are preferred to be continuous.

Local They are related to the private preferences of each driver. Namely:

- Preferences on working hours: morning, afternoons
- Preferences on working days: from Monday to Friday, do not work on Saturday and Sunday.
- Preferences on short/long distances, as for example, one driver that do not like at all to get services from/to Barcelona due traffic jumps.

2.4 Problem formulation

Definition 7. *Driver's allocation problem.* Given a set of services $S = \{s_1, \dots, s_l\}$ required in day x , and a set of drivers D , assign a set of drivers $D^i \in 2^D$ for each service s_i subject to the constraints and preferences described above.

Different solutions are feasible. Each solution sol has a global cost or utility for the company $u(sol)$ that relates the number of constraints violated per each driver, the number of preferences unsatisfied, the drivers cost and the buses cost. The optimization problem consists then on finding the best solution. Formally:

Definition 8. *Driver's optimization problem.* Given a set of services $S = \{s_1, \dots, s_l\}$ required in day x , a set of drivers D , and an utility function u , find the set of drivers $D^i \in 2^D$ for each service s_i subject to the constraints and preferences described above so that u is maximized.

The complexity of the problem is known to be exponential, regarding the number of services requested.

3 Decentralized allocation problem

There are two main research lines regarding decentralized allocation problems: distributed constraint optimization problems [5] and multi-agent resource allocation [6]. Based on our previous experiences [7, 8], we model the problem as a multi-agent resource allocation. Following this approach, the problem is modelled following a multi-agent system in which resources actively participate in computing an allocation [6]. Tasks are distributed amongst a number of agents by following an allocation procedure. In our case, we have chosen a auction approach, mainly due our past experience on it (see for example [7, 8]).

According to [10], auctions are the heart of decentralized resource allocation. The allocation problem for a decision maker is to allocate the resources in an optimal way. Regarding our transportation problem, resources are the driver agents that are assigned to services by a decision maker agent Note, then, that we are distributing tasks to resources (represented as agents).

An overview of the system is the following. At the end of the day, there are a set of services to be performed, that a human operator has entered thanks to a nice user interface. Then, he pushes the start button and the multi-agent system starts. The decision maker agent (auctioneer) is responsible of the allocation procedure. Particularly, it starts a combinatorial auction process from which all the drivers agents are informed of the current requested services. Then, the drivers agents answer with bids. According to the services requested, each driver agent d^i generate a possible partial solution or alternative regarding the tasks that it can perform. Each alternative is a list $(Seq_j^i, u_{hj}^i, u_{sj}^i)$, where Seq_j^i is the sequence of services that the driver can accomplish according to his/her agenda, u_{hj}^i is the utility of the sequence of services regarding hard constraints and u_{sj}^i the one related to soft constraints. For each service, the corresponding initial and end time are also provided.

$$Seq_j^i = \{ \langle s_{j_1}, ti_{j_1}, tf_{j_1} \rangle, \langle s_{j_2}, ti_{j_2}, tf_{j_2} \rangle, \dots, \langle s_{j_{n_j}}, ti_{j_{n_j}}, tf_{j_{n_j}} \rangle \}$$

Finally, the decision maker agent computes the best combination of all the bids in order to determine a final allocation, that is prompted to the human operator through the user interface.

Note, then, that the allocation process is decentralized because each agent computes the utility of its bids regarding private information that is not explicitly known by the decision maker. This is the key difference from previous centralization approaches. However, regarding the allocation procedure in which a combination of bids is selected, this is done by a single agent, the decision maker, in a centralized way.

There are several kind of auctions that depends of different parameters of the problem at hand. Particularly, Parker [10] defines the framework for an auction according to six components: resources, market structure, preference structure, bid structure, matching supply to demand (winner determination), and information feedback. Table 4.1 shows the parameters configuration for our transportation domain.

Before proceeding with the particular description of the parameters in our domain, it is important to clarify the different notation regarding task and resources, since it have different ascriptions in manufacturing, multi-agent resource allocation and the Economic Sciences, the latter being the discipline where auctions originally come from. In this paper we will assume tasks as the items to be auctioned, that is, services to be performed; resources as the agents that actively participate in the allocation process (also called buyers in auctions, or suppliers), and the decision maker the agent that sets the allocation (also called auctioneer, or seller). The auctioneer is characterized by an optimal strategy with which to solve the allocation problem; while resource agents have a valuation process assigned in which they compute the bids with which to participate in the auction process.

4 Auctions framework for road passenger transportation

In this section we resume the different parameters of our problem related to the auctions framework proposed by [10].

4.1 Resources

Resources can be single item or multiple items, with a single or multiple unit each of item. Since there are multiple services to be covered in one day, the road passenger transportation problem is a multiple item type. Regarding the number of units, we assume a single unit for each item, that is, there are no multiple units of the same service.

Multiple item auctions are known as combinatorial auction process, since bidders are allowed to have valuations over bundles of items [10]. Alternatively, if in our domain items (services) are auctioned one by one, there is no guarantee that the last services can be assigned to the still available drives. So combinatorial auctions seems the appropriate framework.

Table 1. Auction parameters for the road passenger transportation problem.

Parameter	Value
Resources	Mutiple Items, single unit
Market Structure	Forward
Preference Structure	Utility function based on time constraints violations
Bid Structure	Multiple Items
Winner determination	multiple-sourcing
Information feedback	Indirect

4.2 Market Structure

The market structure provides the negotiation mechanism between buyers (drivers) and sellers (services). Three main types are distinguished:

1. Forward auctions: there is a single seller
2. Reverse auctions: there is a single buyer, and multiple sellers
3. Double auctions or exchanges: multiple buyers and sellers.

In the road passenger transportation domain we have a single operator dealing with the scheduling process, so we assume forward auctions in order to emulate the current situation. So we are dealing with a forward auction.

Other issues that should be taken into account related to the market structure are side constraints, that are some considerations to take into account in addition to the optimization problem. For example, the number of suppliers that are contracted in the final schedule. In our problem, drivers are one of the most expensive resources. For this reason, minimizing the number of drivers (buyers) is an important aspect to take into account.

4.3 Preference Structure

The preference structure relates to the utility function used for each agent in order to measure the auction outcomes. This is particularly important in the problem we are dealing with. Utility functions are not known by the decision maker, they are private, so this is why the information is decentralized and differs from classical optimization processes.

Regarding our domain, we characterize all drivers with two utility functions: $u_h(a_i)$ that measures the cost of the hard constraints and $u_s(a_i)$ that is related to soft constraints.

On one hand, hard constraints are related to the constraints inherent to the problem and defined in section 2.3. On the other hand, soft constraints are particular to each driver and take into account the particular driver preferences as working hours or days, short/long distances, etc. (see also section 2.3).

Each driver computes both measures regarding the service to be performed, and both measures are used to compute an allocation that maximizes the average utility enjoyed by the agents.

The fact that bids consider more than one attribute, in our case, the hard constraints utility and the soft constraint utility, configure our problem as a multi-attribute auction. The solution should consider a trade off across the different attributes [10].

4.4 Bid Structure

The bid structure specifies the flexibility of agents on resource requirements. As stated in the previous section, our problem presents a bid structure known as all-or-nothing, with an utility given for the complete set of bids. Such kind of structure states that the bids are indivisible.

4.5 Matching Supply to demand

Matching supply to demand, or winner determination, is related to the kind of problem regarding bid selection and the remaining auction features (bid structure, resources, etc.). There are two main sorts: single-sourcing and multi-sourcing. In the former, a single buyer is matched against a single seller; while in the latter, there are multiple buyers or sellers. Consistently, in our problem, we have multiple buyers (drivers) so we are dealing with a multi-sourcing winner determination problem.

Since the market structure has been defined as forward, the multi-sourcing winner determination problem is also known as the set packing problem, known to be NP-hard. However, there are several works, as for example, [11], that argue about the polynomial solution of the problem given some particular topology of the bid space.

4.6 Information feedback

This is an important auction feature, that depends on allowing buyers to adjust bids according to the information gathered in the auction process. So, direct communications do not allow adjustment, while indirect they do.

Regarding our problem, we can imagine a myriad of possible combinations of services that a driver can perform in a given day, any of them with a different utility. Then, two main situations can happen:

1. Agents participate in an auction process with as many bids as combinations can provide.
2. Agents participate in an auction process with the best bid according to their utility function.

In the former case, there can be a huge amount of combinations, so the problem can become quite computationally complex, and even unfeasible. While in the latter, a locally constraint satisfaction process can be required in order to build a single bid with the best combination. This process is also time consuming.

A hybrid approach are handled by iterative combinatorial auctions. If there are n drivers, only n bids will be received by the auctioneer in order to compute a tentative final allocation. As soon as the allocation is known by the agents, they can submit alternative bids. So there is a reduction on the agents valuation work and the optimal strategy performed by the auctioneer.

4.7 Combinatorial auctions for road passenger transportation

According to the previous parameters, our problem fits the iterative multi-attribute combinatorial auction framework. Parker [10] notes such kind of problems are hard to solve analytically, and suggest the use of experimental mechanism designs.

This is one of the reasons why we have chosen an available tool, CASS (Combinatorial Auction Structured Search [12]) to have a first approximation to our problem.

5 Results

We have implemented a first prototype of the system in JADE (see [13] for details) and we have performed several experimental tests with real data coming from a inter-urban transport company, that for confidential reasons we cannot mention here. There were 70 drivers and in average 40 services per day should be scheduled. In each experiment different parameters have been changed : amount of bids per driver, amount of services per bid, and rate between drivers and services. That is, when both, the amount of drivers and services is huge (close to the maximum), the response time of the system is too high. So, we have established a tradeoff between both concepts: when there are few number of drivers, a higher amount of bids per driver are allowed; otherwise, a lower amount of bids per driver are generated. Then, due to the constraint on the number of bids allowed to the drivers, not all the services are covered by the system. Currently, we are working on improving the auctioning process, so we can iterate the process with the non-allocated services.

6 Discussion and conclusions

In this paper we have presented the road passenger transportation problem, and an auction frameworks to approach a solution by means of multi-agent resource allocation. Several auction parameters are analyzed, namely: resources, market structure, preference structure, bid structure, winner determination, information feedback.

The allocation process is decentralized because each agent computes the utility of its bids regarding private information that is not explicitly known by the decision maker. This is the key difference from previous centralization approaches.

The preliminary results shown on this paper point out the computational complexity of the the multi-agent system when dealing with real problems. Further improvements and research effort is required. Mainly, we are interesting on researching on iterative combinatorial auctions, so probably new winner determination algorithm other than CASS should be explored.

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