AN AGENT-BASED APPROACH TO ENABLE DYNAMIC VEHICLE ROUTING IN MILK-RUN OEM OPERATIONS

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RESUMO
O gerenciamento das operações de transporte é uma área interessante para a utilização de sistemas baseados em agentes. Estes agentes, agindo de modo colaborativo, podem lidar com novas informações recebidas após o início dos roteiros, tais problemas são conhecidos como problemas de roteirização dinâmica de veículos (DVRP). Comumente, as pesquisas dessa área se concentram em lidar com novas demandas, desconhecidas durante a fase de planejamento das rotas, abstraindo-se de outras questões dinâmicas, como a presença de congestionamentos ou a retirada de tarefas da rota planejada. Este trabalho apresenta um modelo baseado em agentes para um DVRP em operações de coleta de uma empresa OEM. A transferência de tarefas de coleta entre agentes veículo é realizada através de negociação, o que permite simular estratégias colaborativas entre os agentes. Neste modelo, o agente veículo pode responder autonomamente a mudanças percebidas durante a realização da rota e atualizar autonomamente suas rotas.

ABSTRACT
The management of transport operations is a promising field for agent-based applications. These agents, acting in a collaborative way, can handle new information perceived during the execution of the routes. This process is known as Dynamic Vehicle Routing Problem (DVRP). Traditional research in this field usually focus on new transportation demands, which are still unknown during the routing planning process, ignoring other dynamic issues that may be involved in the operation, as the presence of unexpected traffic congestions and the possible transference of tasks from the regular routes to auxiliary trucks. This article propose an agent-based approach to a DVRP in milk-run OEM operations. The pick-up task transfer process is performed with a negotiation mechanism, which permits to simulate collaborative strategies among the agents. In this model, vehicle agents could perceive changes during the operations and update their routes autonomously.

1. INTRODUCTION
The progress of information and communication technologies (ICTs) has enabled a more intensive exchange of information at lower costs between partnering companies, allowing business performance to improve (Kwon et al., 2008). The acquisition costs of these ICTs have decreased over time, facilitating the adoption of these technologies by people and organizations. This has led many companies to organize themselves into supply chains — the operating structure which is known as supply chain management (SCM) — seen today as a strategic priority for business (Kwon et al., 2008). Frohlich (2002) stated that, in general, integration in the supply chain improves outcomes and provides competitive advantages to firms in the chain. Thus, new businesses have been made possible due to the growth of communication networks, which facilitates access to information and minimizes the impacts of dispersed supply chain members (Soroor et al., 2009).

The dynamic environment in which firms operate, where rapid changes occur in the economy and in new technologies and consumer trends, requires companies to be agile and flexible when dealing with critical situations caused by these changes and unexpected events. These new requirements have led to the emergence of distributed control and intelligent systems, which provide the adaptability and flexibility required by companies. Agent-based approaches are suitable for the management of transportation operations.
Examples of applications of agents in this area can be observed in the studies of Fox et al. (2000), Julka et al. (2002), Karageorgos et al. (2003), Roorda et al. (2010), Vokrinek et al. (2010), and Maciejewski and Nagel (2012).

In general, supply chains are complex systems that are involved in different dynamic, stochastic, and uncertain environments (Long et al., 2011). However, most agent-based approaches do not consider dynamic aspects. In fact, various studies have failed to adequately represent dynamic characteristics and uncertainties (Wang et al., 2008), especially in real-time transportation operations. Thus, to solve such dynamic problems, heuristics are commonly used. Heuristics are problem-solving techniques that do not guarantee a precise optimal solution, but lead to good results in less computational time.

In general, operations research based global optimization methods are used to build transportation schedules. However, such methods have serious limitations that restrict their adoption: It requires a high volume of information a priori, is sensitive to the variation of information, and requires much time to find the optimal solution (Mes et al., 2007).

Optimization methods applied to conventional routing problems are usually not able to handle the sudden changes observed during the development of the travelling process. To address these issues, a class of problems known as dynamic vehicle routing problems (DVRPs) has been developed. The first reference to a dynamic vehicle routing problem is due to Wilson and Colvin (1977), nowadays, some studies have noticed the potential use of recent technologies, like Intelligent Transport Systems (ITS), in transport operations. Pillac et al. (2013) made a review of DVRP applications. DVRPs are concerned with the existence of new events during the operation; thus, they require an immediate operating response in order to perform interventions while executing a preplanned service. Associated with a DVRP, the application of the agent-based framework allows the participants to deal with the various incidents that may arise along the vehicle cycle time, in a timely manner, such as creating and adjusting routes, for example. Agents can make use of operational research techniques to react to these events in a parallel and distributed manner. According to Crainic et al. (2009), this approach allows for prompt and efficient responses in order to change the operating environment.

Davidsson et al. (2005) observed that there are few studies on the use of agents in strategic decision making problems in transportation environments. These authors also stated that the application of the agent approach in this research field still shows a low degree of maturity and of practical possibilities (i.e., the resulting models are far from being operationally applicable in the industry). In general, DVRPs are solved through heuristics and meta-heuristics; however, few research proposals have made use of the agent approach to solve such problems (Zeddini et al., 2008).

So, this study intends to propose an agent-based approach to enable DVRP. The approach is applied to an automaker industry, which is an OEM, i.e., an original equipment manufacturer, which uses logistics operators to perform a milk-run, pick-up service, collecting components and parts at different supplier’s premises, to subsequently deliver them at the automaker plant, in a just-in-time scheme. In the application, there is a fleet of regular vehicles assigned to the picking-up tasks, managed by a firm A, plus a number of auxiliary vehicles, managed by a firm B. Each vehicle is assumed to be an agent. Additionally, firms A and B are also considered as agents, which could have a hierarchical
supervision function over the former agents. The proposed MAS must ensure that the vehicle-agent fleet (regular trucks and auxiliary vehicles alike) collaborate to guarantee at least fraction of non-performed tasks at the end of a daily pick-up cycle. The pick-up task transfer process is performed under a negotiation MAS structure, which permits to simulate collaborative strategies among the agents. Two evaluating criteria are simultaneously used to select a specific collaborative strategy: the service level, represented by the average percentage of performed tasks, plus the average daily operating cost of the vehicle fleet.

The paper is organized as follows: Section 2 presents a literature review of agent-based approaches applied for dynamic vehicle routing problem. Section 3 discusses the important features of the proposed problem modeling, including the collaborative strategies adopted in this study and the scenarios in which the strategies were tested. Section 4 presents the MAS simulation, including the agents used. After that, the simulation results are presented and discussed in Section 5. Finally, Section 6 provides some conclusions and suggestions for future studies.

2. LITERATURE REVIEW

Unlike the classical formulation of the vehicle routing problem, more realistic vehicle routing applications need to deal with changes in the information used after the initial planning of the routes. Psaraftis (1988) defined this problem as a DVRP. According to Pillac et al. (2013), technological advances have contributed to the emergence of real-time routing applications, and such applications allow for fleet tracking and control online. Therefore, a commonly adopted strategy is the use of information produced by global positioning systems and geographic information systems, enabling a spatial perception of transportation operations.

The most frequently studied source of dynamism is the arrival of new requests during the operations, which are characterized by new demands for products or services (Pillac et al., 2013). However, other stochastic variables can be inserted into the problem. For instance, Novaes et al. (2012) developed a model for fault detection that considers the real-time automatic identification of congestion levels, through the sequential analysis of vehicle speed. Other applications suggest checking the availability of vehicles, including possible breaches of vehicles during operation (Li et al., 2009; Mu et al., 2011).

Zeddini et al. (2008) proposed a model that uses negotiation between agents who act in a distributed way. This model is able to cope with new demands and with the removal of already known demands from the route. In this approach, a mediator agent controls the negotiation between customers and vehicles. This agent is responsible for the allocation of demand from clients to vehicles. Therefore, this mediating agent has centralized control, requiring an overview of the current status of all clients and vehicles.

Applying agents to a dynamic problem of collections and deliveries, Wojtusiak et al. (2011) used a learnable evolution model to handle new requests known only after the initial route is planned. This model was concerned with the flow (regular or reverse) of containers.

Two important aspects that determine the degree of dynamism of the DVRP are the time available and the number of events received after the initial planning (Larsen, 2000). With
an understanding of these aspects, it is possible to determine the difficulty in dealing with some uncertainties. The index of dynamism ranges from 0 (purely static) to 1 (purely dynamic). More information about these indicators and their application to problems with time windows can be found in the research of Larsen (2000).

In this present work, the proposed agents must deal with the existence of congestion that is perceived after the start of operations. In addition, vehicles can negotiate the completion of tasks with one another, thus allowing tasks to be included or excluded from the route. Such a feature would hardly be feasible through the manual work of a specialist; it requires the support of an autonomous system that can be supervised by experts.

3. PROBLEM STATEMENT

To propose an agent-based approach, this article takes into account the context of supply to OEM companies (i.e., a carrier must collect high value-added components from suppliers at the end of the work cycle and must deliver the collected components at the automaker premises). Once delivered, the company automaker will handle the assembling of the final products.

In the simulated experiments, a depot of an OEM company, which is located outside of an urban area, received components from its suppliers within the region. Suppliers in an urban area suffer from the impact of congestion frequently observed in these regions on the collection of these components. This application adapted the proposed model by Novaes et al. (2012), which was proposed as a method for scaling the districts. This district modeling differed from the original in the choice of some distribution functions, which govern the speed of the vehicle at normal traffic and congested traffic.

In this application, the level of service is a critical variable, since failures in the pick-up of components may result in critical disruptions in the manufacturing OEM production line, thus resulting in significant costs. Therefore, the fleet size to be used in the operations must be defined accordingly. In this study, the level of service is measured by the fraction of picking-up tasks actually performed. To deal with the high degree of randomness in the variables considered during the transportation operation, the paper evaluates two collaborative strategies: the number of auxiliary vehicles to be used and the negotiation of tasks schemes between vehicles. These strategies aim to improve the level of service obtained by the vehicles, properly managing the possible dynamic events present in these operations.

3.1. Cooperative strategies

Among the cooperative alternatives to deal with several dynamic events in transportation operations, are strategies that aim to reduce the number of tasks not performed at the end of the operating cycle, thus improving the service level. Tasks not performed by regular vehicles are operational problems that should be anticipated and corrected.

The strategies tested are related to two main aspects. First, with the use of an additional number of auxiliary vehicles, the excess of tasks allocate to regular vehicles is transferred to auxiliary vehicles whenever necessary. The second aspect concerns the negotiation between the vehicles (i.e., how to delegate tasks to auxiliary vehicles).
The experiments in this study evaluate the addition of zero to five auxiliary vehicles. In these experiments, the logistics service provider (LSP) asks the auxiliary LSP, at the beginning of the operation, to send auxiliary vehicles to particular locations in the operating region. These initial locations for auxiliary vehicles are predefined, positioning them far apart one from another in the network (Fig. 1).

Fig. 1. Initial location of auxiliary vehicles.

The negotiation alternatives involve the choice of tasks to be removed from the initial route, the calculation of proposals for negotiations, and the method of evaluation and selection of proposals received. Current techniques require agile computing, since there is little time available to react to events during operations.

To select activities to remove, we used the neighborhood operator of removal (Goel, 2008). The procedure suggests removing the job that provides the greatest reduction of the route distance. For each task \( t \) of the route \( R \), the gain from the disposal of a task \( t \) of the route can be verified, thus generating a route \( R^- \). Tasks are excluded from the route until it is potentially feasible. Therefore, the gain from the disposal of \( t \) can be expressed as

\[
\text{gain}^t = \sum_{a \in R} (c_a) - \sum_{b \in R^-} (c_b)
\]  

(1)

where \( a \) and \( b \) are, respectively, arcs of the route \( R \) and \( R^- \), and \( c_i \) represents the cost of the arc \( i \).

In order to calculate the proposals, this work uses the criteria of new remaining distance, the proposal \( bid^t_v \) is obtained for each vehicle candidate \( v \) to accomplish a task \( t \), as presented in the equation 2. Thus, this way of calculating the proposals also contributes to the balance of the distance traveled by each vehicle. The selection of the winning bid is always performed by the lowest evaluated bid.

\[
bid^t_v = \sum_{i=p}^{k+1} (c_i) - \sum_{j=p}^{k} (c_j), \quad a_i \in R^+ \& a_j \in R
\]  

(2)

where \( k \) is the current position of the vehicle \( v \) in the route, and \( R^+ \) is the new route obtained with the inclusion of the task \( t \).
To evaluate each strategy, simulation experiments were performed with the use of agents for the pick-up problem in the context of OEM companies. The Table 1 lists the experiments performed in this study, with information on the identifier, type, number of regular and auxiliary vehicles, and the negotiation mechanism adopted. The experiments were either static (without collaboration) or dynamic (with collaboration). Experiments were evaluated with up to five auxiliary vehicles. The negotiation aims to balance the remaining distance of each vehicle. However, there is no negotiation in Experiment E1, since there is no exchange of tasks between the vehicles and the Experiment E2 exchanges are imposed on an auxiliary vehicle according to the proximity to the center of mass. Therefore, there is no negotiation in this experiment.

<table>
<thead>
<tr>
<th>ID. OF EXPERIMENT</th>
<th>KIND OF SIMULATION</th>
<th>NUMBER OF VEHICLES</th>
<th>NEGOTIATION</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>Static</td>
<td>9</td>
<td>0 NA</td>
</tr>
<tr>
<td>E2</td>
<td>Dynamic</td>
<td>9</td>
<td>1 NA (transfer imposed by the center of mass)</td>
</tr>
<tr>
<td>E3</td>
<td>Dynamic</td>
<td>9</td>
<td>1 Collaborate to balance the distance to travel</td>
</tr>
<tr>
<td>E4</td>
<td>Dynamic</td>
<td>9</td>
<td>2 Collaborate to balance the distance to travel</td>
</tr>
<tr>
<td>E5</td>
<td>Dynamic</td>
<td>9</td>
<td>3 Collaborate to balance the distance to travel</td>
</tr>
<tr>
<td>E6</td>
<td>Dynamic</td>
<td>9</td>
<td>4 Collaborate to balance the distance to travel</td>
</tr>
<tr>
<td>E7</td>
<td>Dynamic</td>
<td>9</td>
<td>5 Collaborate to balance the distance to travel</td>
</tr>
</tbody>
</table>

### 3.2 Scenarios tested

All the experiments presented in Table 1 were performed in different scenarios. Different load levels assigned to regular vehicles were evaluated. In order to simulate the clients and the creation of districts, was adopted used a districting method established in Novaes et al. (2012). So, could be tested scenarios with variations in the load of district sections \{A,B,C\} being tested, namely balanced load \{36,29,25\} (obtained from Novaes et al. (2012)) and overload \{47,34,29\} (adding about fifteen percent). When the load is balanced, the regular vehicles have a low percentage of unperformed tasks. Although low, this percentage may represent an unwanted situation for OEM companies, where delays may cause additional costs throughout the supply chain. In situations where there is an overload of tasks, there is already a high percentage of almost certainly missed tasks. In these circumstances, the inclusion of auxiliary vehicles can absorb much of this excess demand. One must then define how many vehicles would be needed.

### 4. MULTI-AGENT BASED SIMULATION

A multi-agent based simulation is a simulation technique that makes use of agents in simulation models to solve complex problems (Tian e Tianfield, 2006). In general, it is impossible to predict the outcome of the behavior of these agents in the modeling phase. It is necessary to simulate the behavior of these agents in a controlled environment. In the simulation using agents, they may play different roles (Davidsson et al., 2005).

In this approach, there are agents related with the logistics service provider, the auxiliary logistics service provider, and the logistics service provider’s regular vehicles and auxiliary
vehicles (Fig. 2). In this hierarchical control structure, the logistics service provider agent handles a fixed number of its regular vehicles in its fleet. On the other hand, the auxiliary logistics service provider starts a specified number of auxiliary vehicles, and the number of auxiliary vehicles used in each experiment is defined at the start of the experiment. From the beginning of the operation, the regular vehicles can negotiate the transfer of tasks to auxiliary vehicles to reduce the amount of tasks not performed.

![Fig. 2. Structure of agents proposed for dynamic vehicle routing.](image)

The pick-up of components in OEM companies deals with products of high added value. Thus, different requests must be made to collect intermediate products (or components) along the chain. After the products are collected from a particular area, they are transported to the automaker industry, which will handle the final production of the goods that will be consumed by customers.

About the operation of a work cycle (i.e., a day of operation), are involved the logistics service provider agents, the auxiliary carrier, and the logistics service provider’s regular vehicles and auxiliary vehicles. During each cycle, the logistics service provider agent starts its operation, informing its regular vehicles and the auxiliary logistics service provider that a new cycle should start. The cycle is complete when all the logistics service provider’s regular and auxiliary vehicles complete their routes; this control is performed by the logistics service provider agent, which notifies other agents when the cycle begins and ends. The non-viability of the execution of a route is checked during each visit (i.e., after the route has been started). To properly handle dynamic events detected during the execution of the plan, the agents must ensure autonomous responses to events as soon as they occur. An agile response to unplanned events prevents unwanted situations (e.g., collections not held at the end of the daily cycle). For every visit made, the agent vehicle performs a sequential probability ratio test (SPRT) to verify the condition of congestion. Upon detecting congestion, the agent reduces the estimated vehicle route speed to complete the rest of the route. In this case, the vehicle agent may have to transfer part of its remaining tasks to other available vehicles.

5. RESULTS AND DISCUSSION
This section presents the metrics used to analyze the results of the seven simulation experiments conducted in the two scenarios explained in Section 3. Moreover, it presents the main results obtained from the simulation and provides a general discussion about the proposed model.
5.1 Parameters

The model needs to consider the fixed costs associated with transportation operations, enabling the evaluation of the financial results of the simulated experiments. These are associated with the use of vehicles devoted to each route; therefore, as the number of vehicles grows, the fixed costs will increase, regardless of how they are used. Another indicator of this model is the performance of mileage; this indicator relates to variable costs linked to the displacement of each vehicle. Finally, the indicator of extra cost per task performed is not a penalty for not performing a task. Given the overall cost, these penalties should encourage the inclusion of new vehicles to improve the level of service. The values of the parameters that were used in the simulation were estimated in Brazilian reals (BRL) and are presented in Table 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed cost of a vehicle per day</td>
<td>208</td>
<td>BRL</td>
</tr>
<tr>
<td>Variable cost / km traveled</td>
<td>1.12</td>
<td>BRL</td>
</tr>
<tr>
<td>Extra cost for task not performed</td>
<td>100</td>
<td>BRL</td>
</tr>
</tbody>
</table>

5.2 Simulation results

In the scenario without an overload of tasks, the inclusion of an auxiliary vehicle, as in Experiment E2, resulted in a higher total daily cost than that of the static experiment (Experiment E1), although it reduced the percentage of visits not performed. This is because the percentage of visits by the auxiliary vehicle is not large enough to cover the extra cost associated with the inclusion of a new vehicle. Fig. 3 illustrates how the addition of auxiliary vehicles further increases the total daily cost. This occurred in all experiments with auxiliary vehicles in this scenario. The inclusion of auxiliary vehicles also improved the level of service in Experiment E4, which employed two auxiliary vehicles. Subsequently, the level of service can no longer be improved because of two main factors: (1) the level of service is already reasonably high, so producing improvements is even more difficult, and (2) the placement of auxiliary vehicles, which changes with each new additional auxiliary vehicle. These factors may interfere with the outcome of the model.

Fig. 3. Comparison between total average cost and average percentage of unperformed visits for the scenario without extra charge.
In the scenario with an overload of tasks, the large number of tasks not performed considerably increases the total cost of the static scenario, as shown in Fig. 4. In this context, the inclusion of auxiliary vehicles substantially reduces the percentage of tasks not performed. The penalty for not performing these tasks makes the total cost of Experiment E2 lower than that of Experiment E1, even with a higher fixed cost for owning one more vehicle.

When there is an overload of tasks, the inclusion of auxiliary vehicles can handle the excess load of the regular vehicles, leading to a gradual reduction in the percentage of missed tasks. However, in Experiment E7, with two auxiliary vehicles, the total cost begins to grow (i.e., the fixed cost for the additional auxiliary vehicle does not justify the improvements obtained). Thus, the inclusion of two auxiliary vehicles in Experiment E7 proved to be the most interesting option when the average total cost was the criterion for choosing the best experiment.

**Fig. 4.** Comparison between the total average cost and average percentage of missed visits for the scenario with extra charge.

The Fig. 5 compares the results of the two scenarios, namely Experiments E1 (without negotiation) and E7 (five auxiliary vehicles). This figure shows how often missed tasks occur in a given simulated experiment, without an overload of tasks, most of the cycles have a reduced number of tasks not performed (near zero), with arithmetic averages (μ) of 3.28 (without auxiliary vehicles and without an overload of tasks), 1.784 (with auxiliary vehicles and without an overload of tasks), 26.16 (without auxiliary vehicles and with an overload of tasks), and 7.417 (with auxiliary vehicles and with an overload of tasks). Thus, the use of auxiliary vehicles is fundamentally important in reducing the number of tasks not performed, only in scenarios with an overload of tasks. When there is no overload of tasks, the improvement obtained with the use of auxiliary vehicles is not significant.

The Fig. 5 also shows the variation (σ) of results: 2.899 (without auxiliary vehicles and without an overload of tasks), 7,819 (with auxiliary vehicles and without an overload of tasks), 1,891 (with auxiliary vehicles and without an overload of tasks), and 3,961 (with auxiliary vehicles and with an overload of tasks). The use of auxiliary vehicles reduces the variability of tasks not performed (i.e., it reduces the occurrence of a high number of unperformed tasks in the cycle). Thus, the use of auxiliary vehicles reduces the impact of delays in the operation of vehicles. This increased variability in the number of visits made is related to the fact that vehicles negotiate freely throughout the route; therefore, a vehicle can
take on a new task and eventually fail to meet its previously planned tasks.

![Histograms of the number of tasks not performed in all scenarios.](image)

In the scenarios where vehicles have an overload of tasks, the use of auxiliary vehicles is generally not necessary. In this situation, any addition of auxiliary vehicles increases the total daily cost.

The simulations of each experiment were performed on a single computer, abstracting from some technical aspects such as communication and network latency. All the experiments in question were simulated 1,000 times. The indicators of average total cost and average percentage of unperformed tasks were both calculated from data obtained at the end of every cycle simulated in each experiment.

It is important to note that the application was held in a fictional region where the deposit was close to a pick-up area with urban characteristics. Having been designed stochastically with the wedge-shape technique, the results obtained through the application of this model may be valid for other similar situations. Thus, new applications can be implemented with minor adjustments from the originally proposed model. One could do so by an extension of the network representation class.

### 6. CONCLUSIONS AND FUTURE WORK

This study propose an agent-based approach to enable DVRP in milk-run OEM operations, using multi-agent systems, logistics services providers and vehicles could interact autonomously to respond to unplanned events that occur frequently in cargo transportation operations.
Among the collaboration strategies tested, we evaluated the use of auxiliary vehicles to meet the tasks that cannot be met by the regular vehicles. The analysis of results showed that, among other things, the indiscriminate use of auxiliary vehicles can result in unnecessary additional cost, and the auxiliary fleet size depends on the demand attributed to regular vehicles.

The use of negotiation made it possible to test and evaluate collaborative strategies that give vehicles the ability to react autonomously to dynamic events perceived during operations. These strategies were particularly interesting when there was an overload of tasks assigned to the regular vehicles and when they had the support of auxiliary vehicles. In cases where the workload of the regular vehicles was low or there were no auxiliary vehicles, the use of negotiation was not effective, resulting in minimal improvements to the service level.

The evaluation of collaboration strategies between vehicles allows companies to better understand the functioning of distributed decision making, contributing to the adoption of autonomous control methods of transportation operations. Thus, vehicles can respond more quickly to dynamic events, which are present in many urban centers.

The proposed approach in this paper, suitable for the development of MAS, is capable of representing the operation of OEM companies by representing a logistics service provider and its vehicles. Those involved were able to make use of operations research tools to make decisions leading toward their individual goals. However, this study did not consider the existing interfaces with industry. It modeled the demand stochastically, abstracting from the additional complexity of involving these actors.

In future work, new strategies and entities could be integrated into the model as industries and machines involved can be seen as agents. Through the implementation of the agents in the form of web services, something supported by platform used as a basis for the development, this model could be integrated with enterprise systems.

This paper proposed and evaluated some collaboration strategies between vehicles. Different strategies can be formulated and evaluated using this approach. Therefore, this approach can contribute to new developments in dynamic vehicle routing through agents.

7. ACKNOWLEDGMENTS
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