Toewijzen van Lading in Goederentransport met behulp van Machineleer technieken

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Load Allocation in Transportation Logistics using Machine Learning Techniques

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Abstract

In supply-chain management, a fourth-party logistics provider (4PL) is a consulting firm, aiming to optimise the supply-chain and the communication between manufacturers and transportation companies. Manufacturers, producing goods, often outsource transportation activity to a firm, specialised in transportation and logistics. The 4PL, itself, is not asset-based, e.g. it does not provide any physical transportation activity, but is concerned with the orchestration of the supply-chain. The objective of the 4PL consists of adding flexibility in the way manufacturers and transportation companies communicate and agree on a contract. The 4PL wants to reach flexible contract arrangements by using computer systems and intellectual capital to optimise the operations and increase the cost-efficiency of the companies involved. The pressure on the 4PL is very high, as the customers’ demands on fast, cost-efficient solutions are always present.

In this thesis, we propose and elaborate an idea on how flexibility and dynamic service allocations can be achieved by the 4PL. More precisely, the idea consists of combining a bundling technique with an auction house. The virtual auction house allows a very competitive setting, where multiple interested transportation firms can easily connect to and exit. Thus, allowing a very dynamic setting where several, interested stakeholders can be contacted at the same time. The items for sale in the auction house denote so-called transportation requests. These transportation requests represent transportation activities, desired by the manufacturers in the supply-chain, whom wish have their products transported from one location to another. In this highly competitive setting, interested transportation firms can bid on bundles of transportation requests. The bidder of the winning bid is then allowed to perform the physical transportation activity, defined in the bundle.

The goal of the 4PL is to use the advantages the auction house introduces, but at the same time take into consideration the wishes of the transportation firms, in the auction house. In this thesis, we focus on a flexible setting where learning techniques from the area of artificial intelligence are used to incorporate these wishes into the bundles of transportation requests. We investigate how artificial intelligence can influence the current situation in transportation logistics and how it can optimise the work methods of the companies involved. Using experimental settings, we prove that learning how to bundle using machine learning techniques can significantly reduce the expenses, while increasing honest and competitive prices through the auction house. We also examine how this idea can be applied outside the domain of transportation logistics and present a solution approach for a routing problem, involving school buses.
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Chapter 1

Introduction

In the first part of this thesis, we will provide a theoretical overview to inform the reader on the current situation in economics and the delivery process of products, transported from the manufacturer to the end-user, is examined. We will also present the latest proposals in supply-chain management to increase flexible and dynamic service allocations and optimise the flow of work of the companies. The DiCoMas project, which provides a simulator that can be used to run experiments and explore the possibilities of one of the latest proposals, is also clarified.

In the second part of the thesis, we describe how artificial intelligence techniques can be used to increase the performance of the stakeholders of the supply-chain, by making intelligent decisions. We present our ideas and contributions in the implementation study, together with the results achieved.

In the end, we will discuss our work, presenting both the advantages and limitations of our approach.

1.1 Background

In this chapter, we will introduce the principal concepts and background knowledge on transportation logistics. As the thesis is conducted in the economical domain of supply-chain management, we now present its main stakeholders.

1.1.1 Supply-chain management

Supply chain management or SCM, is a systemic, strategic coordination of the traditional business functions used by companies to ensure that their supply chain is efficient and cost-effective. It is considered a management of a network of interconnected businesses involved in the ultimate provision of product and service packages required by end-users [Harland, 1996], as presented in figure 1.1.
Figure 1.1: Supply-chain management consists of different stages, where parts are transported from one location to the other, to be assembled into a final product.

The main idea behind SCM is to decouple the different functions of an organisation to reduce the complexity. Instead of focusing on intra-company decisions, where each department or function includes a lot of dependencies with other departments, SCM wants to decouple these functions into independent components. In this way, the complexity of the decisions is reduced since each component is treated independently of the others. On first sight, these independent components seem the solution to reduce the complexity and to speed up the decision process.

Supply Chain Management can be thought of as the management of material and information flows both in and between facilities, such as vendors, manufacturing and assembly plants and distribution centers (DC). These components can be departments of a large multinational or separate companies that focus on one task. In this setting, goods will then have to be transported over different borders, meaning corporate borders and geographical. To meet the market globalization and decoupling of companies into independent components places high expectations on transport companies that will provide the necessary transport equipment to deliver the goods and parts at the correct vendor at the right time.

SCM is an area that has recently received a great deal of attention in the business community. In the United States, annual expenditures on non-military logistics are estimated at $670 million; over 11% of the Gross National Product. The logistics costs of goods sold, can take up to 30% of the cost of the final product and is not uncommon for U.S. manufacturing firms [Ballou, 1992], thus, potential savings in coordination cannot be ignored. Competitive pressures drive profit margins down, forcing firms to reduce costs while maintaining excellent customer service. Typically, supply chain management is comprised of five stages [Group, 2010b],
as modeled by the SCOR.\footnote{Supply Chain Operations Reference, http://supply-chain.org/about/scor/what/is} SCOR is a product of SSC (Supply Chain Council\footnote{http://supply-chain.org/}), a global nonprofit organization whose methodology, diagnostic, and benchmarking tools help nearly a thousand organizations make dramatic and rapid improvements in supply chain processes. SCC has created the SCOR framework for evaluating and comparing supply chain activities and their performance and lets organizations quickly determine and compare the performance of supply chain and related operations within their company or against other organizations. According to SCOR, the SCM structure can be decomposed into the following elements:

1. **Plan** - This is the strategic portion of SCM. Companies need a strategy for managing all the resources that go toward meeting customer demand for their product or service. A big piece of SCM planning is developing a set of metrics to monitor the supply chain so that it is efficient, costs less and delivers high quality and value to customers.

2. **Source** - Next, companies must choose suppliers to deliver the goods and services they need to create their product. Therefore, supply chain managers must develop a set of pricing, delivery and payment processes with suppliers and create metrics for monitoring and improving the relationships. And then, SCM managers can put together processes for managing their goods and services inventory, including receiving and verifying shipments, transferring them to the manufacturing facilities and authorizing supplier payments.

3. **Make** - This is the manufacturing step. Supply chain managers schedule the activities necessary for production, testing, packaging and preparation for delivery. This is the most metric-intensive portion of the supply chain where companies are able to measure quality levels, production output and worker productivity.

4. ** Deliver** - This is the part that many SCM insiders refer to as logistics, where companies coordinate the receipt of orders from customers, develop a network of warehouses, pick carriers to get products to customers and set up an invoicing system to receive payments.

5. **Return** - This can be a problematic part of the supply chain for many companies. Supply chain planners have to create a responsive and flexible network for receiving defective and excess products back from their customers and supporting customers who have problems with delivered products..
Supply-chain management spans all movement and storage of raw materials, work-in-process inventory, and finished goods from point of origin to point of consumption (supply chain), as shown in figure 1.2. Goods flow from one location to the other, each performing one task that contributes to the final product that can be delivered to the customer.

![Figure 1.2: Flow of goods in Supply-chain management. Source: http://africanlogistics.org/](image)

1.1.2 Logistics

Logistics is a part of Supply-chain management that plans, implements, and controls the efficient, effective, forward, and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customers requirements. Logistics involves the integration of information, transportation, inventory, warehousing and packaging. The purpose of production logistics is to ensure that each machine and workstation is being fed with the right product in the right quantity and quality at the right time. Two important subdivisions of logistics, Third-party logistics and Fourth-party logistics respectively, are explained in the following sections.

1.1.3 Third-party logistics

As we have seen in the previous section, manufacturers need to transported goods between different locations, e.g. factories, distribution centers and customers. Therefore the customer, or also called shipper, needs to contact transport companies that own transport equipment to make sure the products are at the right location at the right time. Such a transport company is called a third party logistics provider, 3PL or carrier.
A 3PL is an outsourced provider that manages all or a significant part of an organisation logistics requirements and performs transportation, locating and sometimes product consolidation activities. In some cases, a manufacturer has its own fleet of trucks to perform all transportation, but often an external company is contacted and manufacturers choose to outsource the physical transportation activity. Outsourcing the transportation activity provides greater flexibility and improved operational efficiency.

Logistics companies are major players on the international, economical market. Over the years, the revenues of transport companies have increased drastically. Peaking in 2008, right before the economical crisis, with a total turnover of $127.0 billion. In 2009, the economical problems have tempered their revenue, while in 2010 the carriers have already recovered, as shown in figure 1.3.

![U.S. 3PL Market 2006 - 2010E (US$ Billions)](source)

Figure 1.3: Although the economy is still recovering from the economical crisis, the 3PL business is still booming. In 2010, their revenue was expected to be $124.1 billion. Source: Basic Industry Group [Group, 2010a]

To find and select the right logistics company for a specific company profile, several websites and techniques [Lau and Goh, 2002] exists, including auction systems to ensure a good price. Long term contracts are negotiated between companies and carriers which imply benefits for both stakeholders. On the one hand, the manufacturers are sure that during a long period, they can acquire the services of a particular transport company, to make sure their goods are delivered correctly so they can focus on the production and assembly processes. On the other hand, the 3PL company is satisfied with negotiating a long-term contract with a shipper, as for the duration specified in the contract, they are sure they will receive a certain turnover at the end of each month. Based on this negotiation, both parties are

\[\text{http://www.inboundlogistics.com/3pl/3pl100_v2.shtml}\]
guaranteed of each other’s services. This contract also provides a certain amount of confidence between the two stakeholders, which helps both to work together efficiently.

Each time the manufacturer or also called shipper, wants to have goods transported from one location to the other, it contacts its transport company (3PL) and provides it with the transportation requests, each consisting of the necessary information to perform the transportation, such as geographical information on the origin and destination and a specific volume. Such an order may consist of a few dozens of individual transportation requests (Fig. 1.4).

On its turn, the 3PL company then constructs a route of pickup and delivery locations for its truck drivers to finish the transportation requests. To make this route cost and fuel efficient, a pickup-and-delivery (PDP) solver is often used. This sophisticated piece of software will try to optimise the route, based on a certain amount of criteria (cost, fuel, respecting the driving hours, etc.) and is a vital part of the transport company as it has a significant impact on its final revenue. If the total number of requests is reasonably small, the situation in figure 1.4 is still manageable. But when the number of shippers (and eventually also the number of requests) increases, the pressure on the planning and coordination services of the carrier companies becomes too large. As planning and coordination is not the main task of transportation companies, there is still room for significant improve-
ments on the work methods on the 3PL’s side. Therefore, as the transportation needs became even more complex, another type of logistics company started to appear that solely focuses on orchestration and coordination. This is the fourth-party logistics provider.

1.1.4 Fourth-party logistics

Where the goal of 3PL companies is to provide the necessary transportation equipment and drivers, the only goal of fourth party logistics or 4PL consists of orchestrating the supply-chain. The division of enterprises into independent departments in order to reduce the dependencies, may be a interesting idea in theory, but in practice, there are some sidemarks to consider. Thomas and Griffin [Thomas and Griffin, 1996] state that in a practical setting, the separation can have costly consequences, as market globalization becomes more and more apparent and there is need for coordination and control of all of their components in order to provide goods and services to its customers at low cost and high service levels. The customers of the 4PL are also referred to as its shippers. They state there is need for an additional component, involved in coordinating the chain of goods, therefore the notion of 4PL was born.

A 4th Party Logistics provider, is a consulting firm specialised in planning the supply chain management and is in close contact with different 3PL companies to put out their transportation requests. The reason why this new phenomenon arose, consisted of the fact that transportation logistics and SCM still represent a very challenging world as coordination and distribution can be achieved by optimisation techniques to improve the performance. For example, as cited by Robu [Robu et al., 2008], in the Netherlands in 2008, the average transport performance was only optimal in about 40%-60% of the cases. Several projects were launched to improve the utilization rate, such as for example the Distributed Engine for Advanced Logistics or DEAL\footnote{http://www.cwi.nl/DEAL} project by CWI Amsterdam, that successfully examined new techniques applicable to the 4PL setting [Amsterdam, 2009]. This explains the importance and the opportunities of 4PL companies when it comes to optimisation. It is also important to notice that there are much more 3PL companies than 4PLs. 4PL is a relatively new concept so only a limited number of 4PL companies exist. Over the whole world, there are only a few companies that focus on planning and distribution, where on the contrary thousands of carriers exist.

The 4PL company acts as a buffer between the manufacturers and carriers, where it aims to find convenient delivery options for the transportation requests of the customers and finally distribute them across carriers that applied for these
orders. This can actually be cheaper than the setting where a shipper contacts one or more carriers individually to arrange a contract, as smaller transport companies often do not have the complex cost structure that larger companies have [Robu et al., 2008, van der Putten et al., 2006]. For smaller carriers it will then be easier to find orders that fit their transport equipment, without overdoing themselves by accepting (too) many orders, which in the end, they can not manage. In short, outsourcing transportation via a 4PL may result in a more cost-efficient solution for a shipper, because arrangements can be sorted more flexible and dynamically.

Another advantage of the 4PL company consists of the fact that it can introduce transparency and fair prices in the supply-chain, which is at the moment a serious problem as no institution exists that investigates and regulates the prices. Thus, nothing stops the 3PLs in charging exuberant prices and invoices. When, for example, a shipper contacts a 3PL directly and it tries to arrange an order to deliver good X over a distance of 1500 km, from Brussels to Madrid, the transport company, with their depot also located in Brussels, can then choose itself what price to ask to perform this task (see figure 1.5). It does not have to provide the client with additional information of the price setting or explain the reasons behind the price and therefore nothing prevents the 3PL company to lie about it. A 3PL could argue that the truck has to drive 1500 km empty when it returns from Madrid to Brussels in order to set a high price. There exists no opportunity to actually check this statement when a 4PL company is not used a buffer.
Figure 1.5: A shipper contacts a transport company on its own to transport a good from Brussels to Madrid. The 3PL company places a certain price on this order, without giving any indication whether this order actually fits very well or very bad between its other orders of the day. The price can be very high as the company can state that 1500 empty kilometers have to be driven to return to the home-station. The customer has no other choice than to accept the price and is obliged to pay. Source: http://maps.google.com

Due to the fact that internal details of the firm can be hidden very well, the transport company may in fact increase profits without additional expenses. Imagine that another client asks to pick-up a certain good Y at Madrid and deliver it to Reims, in the North of France. The transport company can then once again pretend to state that the order does not fit in their schedule and ask a very high price. On the contrary, their pick-up and delivery solver, mentioned earlier, will easily combine (figure 1.6) the two orders (Brussels → Madrid → Reims → Brussels), resulting in only 500 km of empty truck load, significantly reducing the 3PL’s expenses and earning double on the two transportation requests.
Figure 1.6: By combining the two orders, the 3PL company can reduce its empty kilometers and in absence of a 4PL company, it can in fact earn twice as much as both customers do not know about each other and the lack of planning and coordination drastically increases their cost. Source: http://maps.google.com

When the 4PL company emerges, the communication between customer and carrier becomes indirect, as the 4PL will behave like an additional component taking care that the planning and the distribution of the transport orders between the different carriers. As depicted in figure 1.7, shippers (customers) provide the 4PL company with its requests. This is typically done on a daily basis and may cover hundreds of requests that have to be scheduled and assigned in less than a day’s time. Compared to the few dozens of requests the 3PL would need to arrange on its own, in absence of a 4PL instance, this would be a much harder task.
Figure 1.7: Illustrative presentation of the indirect communication between manufacturers and 3PLs, when a 4PL component is used as a buffer. In the literature, proposals on how the 4PL should accomplish its goals through indirect communication are rare, therefore, at the moment the behaviour of the 4PL in supply-chain management is still vague.

In fact, the 4PL acts as a regulator institute that preserves an overview on the input, the hundreds of transportation requests and the output, the assignment of these requests to the carriers. Because of this central component, mechanisms can be constructed to guarantee (a) fair and honest prices for the customers and on the other hand (b) optimal allocations of the requests to the 3PLs. Thus, both (a) and (b) are the objectives the 4PL wishes to realise and the idea of a 4PL is considered very promising to increase the cost-efficiency in the supply-chain. Nevertheless, as the idea behind the proposal of the 4PL is relatively new, details on how the 4PL institute should obtain an organisational coordination and orchestration of the supply-chain are limited or not published. In the section 1.3, we will elaborate on one of the latest proposals on how to he 4PL should introduce trust and fairness through coordination and discuss the research objective of this thesis in section 1.4.

1.2 Problem description

After specifying the domain in which this thesis is situated, together with its main stakeholders, we can now present the problem description. As already mentioned in 1.1.4, the introduction of the 4PL is one of the ideas proposed to increase trans-
parency in the communication between manufacturers and carriers in the supply-chain. As we have seen, due to the lack of control and management in this communication, competitive invoices and an optimal assignment of transportation requests to carriers is missing. Thus, the problem description of this thesis consists of defining the 4PL’s behaviour that can ensure fair prices and qualitative resource allocation. In the literature, the 4PL’s problem has not been covered or discussed thoroughly. To the best of our knowledge only one idea has been proposed by Robu, which is discussed in section 1.3.

1.3 Related work

In this section, we will present and discuss previous work conducted in the domain of our problem description. As already mentioned, research on how the 4PL should obtain advantages for both manufacturers and carriers is very rare. One of the most specific ideas is proposed by Robu et al [Robu et al., 2008] and consists of negotiation techniques. Furthermore, we will also discuss the work by Vanovermeire [Vanovermeire and Sorensen, 2010] where a solution on horizontal collaboration is proposed to solve the coordination problem in the supply-chain.

1.3.1 Negotiation

As we recall, the objective of the 4PL company consists of distributing items (transportation requests) amongst transport companies that, in the end, will pick-up and deliver them at the right locations. Communication between 4PL and 3PLs are necessary to come up and discuss the contract involved in this cooperation of the two companies. Robu [Robu et al., 2008, van der Putten et al., 2006] proposes a negotiation technique to allow communication between 4PL and 3PL. They focused on closed-group negotiation, is shown in figure 1.8, where a large amount of the orders (i.e. around 80%) received by the 4PL company are currently not auctioned off to an outside market, but are allocated among a small group of trusted 3PL carriers, where they negotiate the value or the price asked to perform an order. A small subset of the orders, i.e. around 20% is offered on the "open market", via transportation matching website such as Teleroute ⁵. On these sites, there are no barriers of entry or so called admission rules. In their research, they concentrated on the first set-up, the closed negotiation, chiefly because it had a higher business-impact and 80% of the orders are allocated in this way. Their approach consists of negotiating in agent-mediated electronic markets that transcend the sale of uniform goods. They believe that, through negotiation [Robu et al., 2005, Robu and Poutré, 2005], suppliers and consumers can

⁵http://corporate.teleroute.com/
reach complex agreements in an iterative way, which better matches the needs and capabilities of different parties. In more detail, they create an explicit model of the buyers utility function, in the form of a utility graph. Robu et al. were supported by Vos Logistics, a 3PL located in Holland, to provide real-life data of 6000 transportation orders.

Their approach works by dividing the one-to-many negotiation between the 4PL and 3PL companies from the closed group in a series of one-to-one negotiation threads between proxy-agents [Kersten and Lo, 2001], representing a company (3PL or 4PL). Their model is constructed from information, gathered from previous negotiations in order to aid buyer modeling in future negotiation instances, this is called the dataset of previous negotiations. A schematic overview of their approach is presented in figure 1.9. They state that the advantage of their work is that no human input is needed in order to achieve efficient outcomes, by using techniques derived from collaborative filtering (widely used in current e-commerce practice) to learn the structure of utility graphs used for such negotiations.
Their results have stated to reduce the company's cost by 19% if their model is adopted and used in practice. In order to protect the competitive advantage of VOS Logistics as well as the privacy of their customers and associates, much of this analysis was not reported and therefore could not be used in our thesis as a comparison.

One of the final remarks that Robu et al. state consist of the fact that at the moment of writing, open-group negotiation is a challenging area of the problem that has not been fully explored yet. More precisely, they state that “auction protocols would probably be more suitable for open-group negotiation, as here all agents are strictly competitive and there are no barriers of entry”.

Figure 1.9: Top-level view of Robu’s agent architecture and simulation model. Source: [Robu and Poutré, 2005]
1.3.2 Horizontal collaboration

Vanovermeire states that companies increasingly feel the need for more sustainable transportation. Their supply-chains are no longer only judged on cost efficiency and on-shelf availability, but parameters such as traffic congestion, CO2-emissions and energy consumption become increasingly important. To be able to respond to this evolution, companies can improve their efficiency and sustainability significantly on their own, but they will need to collaborate in order to be able to comply with the more stringent demands of the government and their clients. This is called horizontal collaboration.

The main barriers that impede collaboration are finding and trusting appropriate partners, determining and dividing the gains. This, together with difficulties during the negotiation process and the absence of the right coordination and ICT-mechanisms [Vanovermeire and Sorensen, 2010]. Vanovermeire et al. focus on the point of view of the 3PLs in the supply-chain and propose a definition of an appropriate cost allocation mechanism to ensure the gains are divided fairly. They state that flexibility needs to be integrated into the operational planning and cost allocation to be able to use the potential of the horizontal alliance to the fullest.

Their work differs from a forwarder, which tries to optimise the flow of goods in the supply-chain. Bundling of orders from a forwarders side can only be achieved in an ad-hoc manner: orders can only be bundled together if they happen to have the same delivery date and fit together in the same truck. Horizontal collaboration, on the other hand, enforces carriers to actively search for more synergies. For example, they can synchronise their orders (adjusting delivery dates) or change the size of their orders to create more compatible orders. When companies allow changes to their orders in order to decrease the total cost of the consolidated supply chain, they denote this as companies being more flexible and thus needs to be encouraged.

They state that the benefit/cost allocation is a vital factor when incorporating flexibility, as it determines whether companies will allow certain changes and therefore, the optimisation problem should consider the planning and cost allocation simultaneously. Although a wide variety of profit and cost allocation mechanisms exist and have been developed, co-operative game theory and more specifically the Shapley value are recurrent solutions for the cost allocation problem [Leng and Parlar, 2005]. The Shapley value [Hart, 2002] is proposed as a mechanisms from the field of game theory that finds a perfect application in supply-chains, as these consist of companies that each make their own decisions, but their decisions influence the total supply-chain performance (and their own). The
The Shapley value determines the cost $c_i$ that needs to be allocated to a player $i$ in a coalition of size $n$ by taking the weighted average of the marginal cost of player $i$ in each possible subcoalition $N \setminus i$. In other words, to each possible subcoalition that can be made without player $i$, that player is added and the extra cost that each of these additions cause will be used to calculate the cost that needs to be paid by this partner.

Thus, using Shapley the value of or impact of a partner can be determined, implicitly incorporating flexibility. Flexibility on its turn increases the probability on synergies, a partner that allows flexibility will probably have a lower marginal cost when added to a (sub)coalition than a rigid partner. Shapley can be used as an operational planning tool without knowing the cost for each partner to be more flexible. Companies have an incentive to represent their internal costs and flexibility options as accurately as possible. As a lying company would deny itself optimisation and profit possibilities.

The work of Vanovermeire is focused on investigating the fairness and flexibility of the carriers, through Shapley. Nevertheless, their work is still ongoing and clear results on the performance of their techniques are not published yet. Until then, fairness is still very subjective matter and there is no clear answer which profit allocation method is the best.
1.4 Proposed approach

Our subject of research will aim to cover another technique than the one presented by Robu [Robu et al., 2008, Robu et al., 2005, Robu and Poutré, 2005], where negotiation between stakeholders is used to come up with agreement between the shippers and the transport companies in a SCM environment. In this section, we will cover in detail our approach and elaborate on the research objectives of this thesis.

1.4.1 Definition of research topic

As specified in the problem description in section 1.2, our work is situated in the world of the 4PL, where we are aiming to define and examine the possibilities of communication between 4PL and the carriers in the supply-chain. The research objective of this thesis consists of investigating the possibilities of adding bundling behaviour in the 4PL, in combination with an auction house.

The detailed behaviour is defined as follows; the manufacturers, and thus the customers, pay the 4PL a certain price, called \( P_{\text{customer}} \) to coordinate and plan their transportation requests. On its turn the 4PL organises a pool of transportation requests that it receives from different customers, which it uses to create subsets or small groups of requests that can be auctioned off in a so-called auction house. In this auction house, agents, representing interested carriers, can connect and place bids, referred to as \( B_{3PL} \), on the bundles, being auctioned. These bids represent the price or invoice the 3PL demands and reflects on the 3PL’s expenses. For example, if the cost of physically transporting a bundle is high, chances exist that the 3PL will charge a very high price or will even refuse to place a bid. The lowest bid in the auction house for a bundle is the winner and is allowed to perform the transportation activity. Different auction techniques exist and are elaborated in section 1.7.1.

The introduction of the auction house, which works in close collaboration with the 4PL, enforces an open-market negotiation, as suggested by Robu et al. in section 1.3.1. Thus, instead of relying on one-to-one negotiations, in the auction house, the setting of one-to-many negotiations will be examined. One of the problems with one-to-one negotiation on a large scale, consists of the problem that the competition between the 3PLs is omitted and the rivalry between these companies can not be exploited. In an auction house, the bids are often sealed, which means that the bidders do not know which other bids are placed and thus, competitive and low bids are a result.

The 4PL on the other hand, will concentrate on allocating the transportation requests from the different shippers, by creating a pool of transportation order. Out of this pool, with a lot of diversity, the 4PL’s focus lies on obtaining bundles of
transportation orders that are desirable and popular by the bidders, in this case the carriers. As the 3PL’s bid reflect on its estimated cost for a bundle, the objective of the 4PL consists of bundling items in a cost-efficient way which results in low bids in the auction house. The utility function of the 4PL is presented in 1.2. As mentioned earlier, the variable representing the price the customer pays the 4PL to coordinate and plan its orders is $P_{customer}$. By bundling in accordance to 3PL’s preferences to reduce their costs, the goal is to diminish its bid in the auction house, $B_{3PL}$. In this way, the utility of the 4PL, e.g. its profit, will be maximised.

$$U_{4PL} = P_{customer} - B_{3PL}$$

Bundle preferences for the 3PLs, involved in the auction house, vary a lot. An example of a preference is in fact already explained in section 1.1.4 where return shipments reduce the company’s expenses drastically. In our proposal, the 4PL’s bundling software could foresee the situation described in figure 1.5 and 1.6 and combine the two requests into one bundle. The shippers pay the 4PL company a certain price to coordinate and plan their requests and the 4PL company on its side ensures a certain amount of optimality and ensures that every request is assigned to a certain carrier. Another example of a preference could be one informs you that the 3PL’s trucks can only carry up to 10 tons. This is be considered a preference of the 3PL company and it would be wise to exploit this information and group request items in to bundles up to this weight and not beyond it, as this would increase the number of trucks needed to cover the bundle, and therefore also the cost of the carrier company. Bundling in accordance to the general preferences of an audience of carriers is not a trivial task and will also attract a lot of attention in this thesis. Especially because of the limited amount of available information the 4PL can rely on to create these bundles. This difficulty will be explained in 1.5.1.

The proposed behaviour for the 4PL component in the supply-chain, is illustrated in figure 1.10. Out of a pool of transportation orders of different types and customers, the 4PL wants to bundle in accordance to the preferences of its bidders. This, to reduce the 3PL’s cost and increase its own profit.
Figure 1.10: The fourth party logistics company provides a necessary organisation of delivery transportation requests to 3PL companies, with great interest in making reducing the costs by creating low-cost bundles.

In the thesis, we have separated the behaviour of the 4PL into two parts. First, a model will be constructed that consists of knowledge on 3PL’s preferences. To accomplish this, information will have to be gathered and deducted from the bidders, which are in close relation with the auction house. A second objective of the 4PL is to use this knowledge as a guidance to construct bundles. This, while being aware that the knowledge gathered can be falsely and will have to be adapted all the time to meet the 3PL’s preferences. A schematic overview of the separation of the problem given in figure 1.11. Other difficulties and complications with this approach will be covered in section 1.5.
In the end, we also want to evaluate our work, to be able to compare it versus other techniques and actually form a consistent conclusion. To allow this, metrics should be constructed that take into account the bundles and the cost of the 3PL companies. As we move along the learning process, we want to see a reduction in the cost of the carrier companies as this would be a clear indication that learning how to bundle can be used as a cost reduction technique.

1.4.2 A daily routine

In earlier sections, the proposed approach with the collaboration between 4PL and auction house to distribute transportation orders to different carriers has been described. Instead of letting the manufacturers provide the carrier companies with a few dozens of orders, the additional 4PL component introduces a different way of working. This approach can be denoted intuitively via a scenario, representing the daily routine of these companies.

1. Receive the orders of the manufacturers

2. Create bundles out of the individual requests, based on a model, representing knowledge about the ‘buyers’ of the bundles

3. Auction the bundles of towards these buyers, e.g. the 3PLs
4. Learn from this experience and update your model, based on the bids in the auction house.

5. 3PLs perform the transportation requests.

This enumeration can be represented visually using a sequence diagram.

Figure 1.12: The sequence diagram shows the tasks and interactions between the different parties in the SCM.
Using a finite state machine (FSM), which is composed of a finite number of states and transitions between those states, we can focus on the behaviour of the 4PL (figure 1.13).

Figure 1.13: Using a FSM, the behaviour of the 4PL company in planning and coordinating the supply-chain, can be presented in a graphical notation. This behaviour is characterised by a final number of states and transitions between the states, which represent actions of the 4PL.
1.5 Challenges

It should be noticed that the research topic, defined earlier, consists of a rather general idea that might not be specific enough. Before we can state the research objectives, that will extend the research topic, we will now present the main difficulties and challenges with our approach. This, together a few solution proposals that will be included in the final research goals.

1.5.1 Logistics companies

The main problem concerning the 3PLs in this approach is the limited amount of data available and their indeterministic way of working. As we have seen, the degree to which a bundle is interesting to a certain 3PL company is influenced by a lot of factors. These factors can range from the amount of trucks the company owns and the quantity needed to cover a certain bundle, to the current fuel prices or the unstable economical situation on the international market and much more. The problem is not that we could not create a system that takes into account all these properties, but the lack of this data is the major concern. When we recall figure 1.10, we remember that the 4PL arranges a certain price for a bundle of transportation requests, based on an auction between different 3PLs. These 3PLs place their bids on the available bundles, based on one of the auction techniques, mentioned in section 1.7.2. Some of these techniques imply an open or closed auction, where bids are announced in public or concealed, respectively. None of the auction rules or even laws in general oblige 3PL companies to place honest bids or bids that represent their business’s preferences. In short, nothing prevents 3PL companies to lie about their expenses, influencing the price they set on a bundle and this implies difficulties for the coordinator of the supply-chain.

Another difficulty, next to possible dishonesty of the carrier companies, is the lack of data defining their preferences. No one forces the 3PL companies to present their preferences and what they are looking for in a bundle. In the first part of the example presented in section 1.1.4, where a transport company was already presented with a request involving the transport of a good from Brussels to Madrid, it would be of a great practical value if the 3PL would announce the fact that it already possessed a request with those coordinates. If this would be the case and the 3PL provided the coordinates, i.e. the 4PL with this type of information, it could easily arrange another request that would allow a best-fit for the carrier company, reducing the empty kilometers of the truck. Both parties would then be satisfied as the 4PL has got one request less to assign and the 3PL reduces the distance it has to cover with an empty truck, which would imply a good price and reduction of costs for both stakeholders. Nevertheless, at the moment, the 3PL companies are not eager to reveal their preferences and internal information as it
is thought of as a privacy violation and therefore the feedback information is very poor and limited to the prices they bid in the auction system.

Nevertheless, the only feedback information the 4PL receives, via the auction house, from the 3PL side of the proposal, consist in fact of bidding information. Figure 1.14, shows this work method in an illustrative way; carriers bid on bundles created by the 4PL, but the only information returned to the 4PL is the winning carrier company, together with the value it has set on the auctioned item. In the best case, multiple bids are collected, but as presented in 1.7.2, other auction techniques exist that provide only one bid, which diminishes the useful information even more. In short, we can state that the only information floating back to the 4PL, is the price that was set. Using this limited feedback, the 4PL should deduct preferences of the different bidders to construct interesting bundles for them, resulting in a reduction of their costs.

Figure 1.14: The only feedback information the algorithm can use to learn which properties of bundles are important and which preferences of the 3PLs play a significant role in the calculation of the bids, are the bids themselves, recorded in the auction house. Only the winning bid and bidder and some possible other bids are recorded.
Thirdly, no information is available on the specifications of the trucks and the location of the depot of the carriers (figure 1.15). Although, it is obvious they play a major role in the price setting. If this would be the case, the 4PL could rather easily bundle items close to each depot, and these bundles would contain excellent distance characteristics. Sadly, this is not the case and one will have to rely on other techniques to extract preferences of the participants in the auction house. We recall that the reason the 4PL wants to bundle interestingly for its carriers, is to enlarge its own profit, as mentioned in 1.1.4. This is considered a very difficult task, as the only feedback is in fact the bidding information and no heuristics can be used to guide the search towards interesting solutions.

![Diagram](image)

Figure 1.15: The 4PL is not provided with information of where did a certain price come from. Also, the trucks and their location is not known.
A possible solution approach to still conduct preferences and other details on the 3PLs in the auction house, consists of applying artificial intelligence and machine learning techniques. Artificial intelligence or A.I. techniques could be able to deduct and infer 3PL preference, using the minimal information available, e.g. the bids. Details on how one can apply A.I. in the field of supply-chain management to deduct preferences, has, to the best of our knowledge, not been examined or investigated before, but is considered a challenging approach. These concepts are further explained in section 1.7.4 and 1.7.5, respectively.

Multi-objective setting

Another difficulty that the research topic introduces is the multi-objective setting of the problem. This lies in the fact that the 4PL’s task consists of distributing transportation requests across carriers and this, while taking into account the costs involved in this process. The goal of the bundling software is to minimise certain cost criteria to make the bundles appear attractive to the bidders in the auction house. This task consists of a search towards optimal bundles and is already a challenging job on its own, but additional requirements in the contract between manufacturers and 4PL state that no transportation request should be left unassigned to a carrier at the end of the day. This introduces implications on the bundling behaviour of the 4PL, meaning that it should posses facilities to rebundle any unassigned transportation requests and make sure the contract is lived up to. The part of the bundling problem is referred to as the problem of finding a complete coverage or allocation for all requests. This, together with the difficulties introduced by the limited available data (section 1.5.1), introduces additional requirements to the bundling system we will elaborate on in this thesis.

1.6 Research objectives

After defining the research domain and proposals, in section 1.4.1 and the difficulties or challenges involved, in section 1.5, we can now describe the research objectives of this thesis in full detail.

As specified, an indirect communication management system will be investigated in this thesis. This, by applying a bundling approach in close cooperation with an auction house. The 4PL receives the transportation requests from the manufacturers or shippers, which become its customers. Out of this database of requests items, the 4PL creates groups or bundles that will be fed into the auction house, where agents, representing interested 3PLs, can place bids. The goal of this thesis is to examine how this bundling approach can be applied in an intelligent manner.
Thus, instead of creating random bundles, the objective of this thesis consists of creating bundles the 3PLs considered interesting or desirable. Because of the limited information available, as discussed in section 1.5, the carriers do not provide information on what they desire in a bundle of transportation requests or what criteria make a certain bundle popular or not. In fact, only bidding information can be used to deduct or infer preferences, such as for example volume or distance specifications. Only relying on this minimal feedback information introduces noise and a lot of approximations in constructing a model or hypothesis on the specifications of preferences of a bundle’s criteria. As we have proposed, artificial intelligence and machine learning techniques could provide a solution approach, able to generalise this hypothesis, despite the noise. Although, previous work on this subject, together with artificial intelligence techniques has not been attempted before, as literature on this topic is very rare.
1.7 Related concepts

In the previous section, we have elaborated on the domain of the research problem and a proposed solution approach, together with its difficulties. We also covered the research objectives of this thesis in full detail. Now, it might be interesting for the reader to already become familiar with the main concepts of behind this proposal, such as the auction house, pick-up and delivery problems and artificial intelligence.

1.7.1 Auction house

In economic theory, an auction is mechanism or set of trading rules for exchange. More precisely, an auction is a process of buying and selling goods or services by offering them up for bid. In the auction house bids are recorded, and the item, being auctioned is sold to the highest bidder. There are several variations on the basic auction form, including time limits, minimum or maximum limits on bid prices, and special rules for determining the winning bidder(s) and sale price(s). Participants in an auction may or may not know the identities or actions of other participants. Depending on the auction, bidders may participate in person or remotely through a variety of means, including telephone and the internet where agents represent companies and bid in accordance to the company’s interest. In the following paragraph, section 1.7.2, the different types of auction techniques are covered.

1.7.2 Auction types

In real life, there exist several different techniques involving the manner the auction is coordinated and winners are assigned. In short, we will examine the main types of auction and their practical considerations.

- English Auction - In an English auction, the auctioneer first describes a starting price (or reserve) for an item on sale. This represents the minimum price asked. Buyers with a possible interest in the item can then announce how much they want to offer for the good and a bid is accepted, only if it is higher than the current highest bid, which is called the standing bid. This is the reason why it is called an open ascending price auction [McAfee and McMillan, 1987]. The item is assigned to the bidder with the highest bid if after no competitive bidder challenges the standing bid for a certain amount of time. In practice, this auction type is often used for example when auctioning works of art.
• Dutch Auction - The Dutch auction\textsuperscript{6} is considered an open descending price auction [Bagwell, 1992]. Instead of announcing a reserve (minimum) price, the auctioneer starts with a high asking price which is lowered until a bidder is willing to pay the price. This type of auction is interesting when a large amount of goods have to be sold quickly, since a sale never requires more than one bid. In practice this auction type is often used to auction flowers and vegetables.

• First-price Sealed Bid Auction - This is a closed auction [Milgrom and Weber, 1982], where bidders announce their (only) bid in a concealed fashion. When all bids are entered, the bids are examined and compared to determine the bidder with the most interesting price, i.e. is the highest price.

• Vickrey Auction - Or, also called Second-price Sealed Bid Auction, as this is identical to the sealed first-price auction except that the price payed by the winning bidder is the second highest price [Vries and Vohra, 2000]. This auction type has proven its importance in theoretical studies, but is rarely used in practice [McAfee and McMillan, 1987], except for Ebay\textsuperscript{7} that uses it. The winner then pays the second highest bid plus a bidding increment (e.g., 10%).

1.7.3 Pick-up and delivery problems

As already mentioned in 1.1.3, the manufacturer wants to have its goods picked-up and delivered at the right location. It therefore contacts the 3PL company to physically transport the products from one location to the other, respecting the truck’s capacity, fuel consumption, maximum amount of driving hours of the truck driver, etc. To find an optimal (or close to optimal) route between the different locations, the company uses a pick-up and delivery problem (PDP) solver to explore the thousands of combinations of routes possible, to come up with a good solution, taking into account the criteria mentioned earlier, thus reducing the company’s cost. Pick-up and delivery problems cover a significant share of the thesis and therefore it is worth mentioning its relevance and the details behind it. In mathematics and computer science, the PDP is a well known problem, that is already examined a lot. It is proven to be an NP-hard problem [Garey and Johnson, 1990], and can furthermore be characterised by the following definition [Savelsbergh and Sol, 1995]:

In the General Pickup and Delivery Problem (GPD) a set of routes has to be constructed in order to satisfy transportation requests.

\textsuperscript{6}http://www.epiqtech.com/auction_software-Dutch-Auction.htm
\textsuperscript{7}www.ebay.com
A fleet of vehicles is available to operate the routes. Each vehicle has a given capacity, a start location and an end location. Each transportation request specifies the size of the load to be transported, the locations where it is to be picked up (the origins) and the locations where it is to be delivered (the destinations). Each load has to be transported by one vehicle from its set of origins to its set of destinations without any transshipment at other locations.

Figure 1.16 describes the input of a problem instance of the PDP on the one hand side, consisting of different pick-up and delivery locations, where goods have to be picked-up and delivered, respectively. The goal is now to construct a route for a truck that covers all locations, respecting the fact that goods first have to be picked-up before they can be delivered and that a truck can only transport one good at the time, at least in this illustrative example. In real life, this is of course not (always) the case. In the literature, the problem of solving pick-

Figure 1.16: On the left hand side, we see the an illustrative representation of a pick-up and delivery problem instance, where the starting location, or depot is denoted by a red triangle. The goal of solving this problem instance (for a single vehicle) is to come up with a route assignment that optimise’s the company’s cost. On the right hand side, we see a solution for the problem instance, where a route, consisting of a sequence of pick-up and delivery locations, has been found that minimises the costs. Source: M. I. Hosny [Hosny, 2010]

up and delivery problems has been tackled by many researchers [Irnich, 2000, Mitrovic-Minic and Laporte, 2004, Xu et al., 2003], using different techniques, such as local search [Bräysy and Gendreau, 2005], swarm intelligence [Ankerl and Hämmerle, 2009], genetic algorithms [rong Jih and jen Hsu, 2004] and much more. Therefore, it is
no longer a real challenge to cover this subject in detail in this thesis, but it still is considered an important component of the way 3PL companies work and compute their prices and costs, and therefore it is worth mentioning.

1.7.4 Artificial intelligence

A part of our proposed approach and our thesis consists of enriching the behaviour of the 4PL with artificial intelligence. Therefore, we find it important to explain the background of this part of the thesis, together with some techniques it comprises.

Artificial intelligence or A.I. in short, is a branch in computer science, aiming to let machines or computers (called agents [Russell et al., 1996]) behave intelligently. According to Russell & Norvig, an agent is anything that can be considered perceiving its environment through sensors and acting upon that environment through actuators. This simple idea is illustrated in Figure 1.17. The goal of A.I.

![Impressionistic Overview of an Intelligent Agent](image)

Figure 1.17: Impressionistic Overview of an Intelligent Agent. Source: [Russell et al., 1996]

is to let the system behave rationally, this means that for each possible percept sequence, a rational agent should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has. Mathematically speaking, we say that an agent’s behavior is described by the agent function that maps any given percept sequence to an action. A.I. techniques cover a wide range of tools that can be used to construct a reward-function of an agent, mapping input from its sensors, to the correct output via its actuators.

At first, A.I. may seem irrelevant for the context of transport logistics or economics in general. We tend to believe that computer’s lack the capability to act in a complex environment, such as the economical market, where a lot of actors behave differently, each trying to maximize their own utility or profit. Artificial intelligence and learning techniques are very applicable in situations where classical, analytical methods become irrelevant. These situations comprise complex
settings with large problem spaces where analytical methods are not able to find a solution for the problem in reasonable time. [Wellman, 1995] states that the world economy is such a complex setting, where the goals of A.I. and those of economics overlap substantially, and are analogous in many of the non-overlapping regions. Thus, economical applications of artificial intelligence will become more and more present in companies involved in the economical market [Wellman, 1993], where they can for example replace humans in the decision making in stock markets, called algorithmic trading [Hendershott and Riordan, 2009].

1.7.5 Machine learning

Artificial intelligence covers a very wide area in computer science. In detail, we will focus in this thesis on machine learning techniques. Machine learning (ML) is the study of computer algorithms that improve automatically through experience [Mitchell, 1997]. Applications range from datamining programs that discover general rules in large data sets, to information filtering systems that automatically learn users’ interests. Machine learning can be organized into a taxonomy, based on the desired outcome of the algorithm. The main branches represent:

- Supervised learning - A teacher presents a learner with a series of training examples and the label associated with it. The learner tries to see patterns in the training data and tests what it has learned on unseen examples. For example classification. More details on supervised learning can be found in section 3.1.3.

- Unsupervised learning - A system tries to determine how data is organised, without the help of a teacher, e.g. clustering. More details on unsupervised learning can be found in section 3.1.4.

- Reinforcement learning - Learns how to act given an observation of the world. Every action has some impact in the environment, and the environment provides feedback in the form of rewards that guides the learning algorithm. For example, an agent trying to learn to a policy of how to act in certain situations. More details on reinforcement learning can be found in section 3.1.5.

In practice, there have been a lot of successful applications of machine learning. For example; speech recognition using the SPHINX system [Lee et al., 1989], autonomous driving (ALVIN system) [Pomerleau, 1991], learning to play backgammon on a world-class level [Tesauro, 1995] and much more.
Learning systems

In this section, we will elaborate on the principles of computer-based learning and the approaches involved in more detail. We also present a general formulation to ML problems and solutions to these problems.

Learning in a computer program can be defined by improving its performance at some task through experience. Put more precisely, Mitchell [Mitchell, 1997] states that:

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

For example, imagine we are trying to build a ShopBot, a computer program that aims to learn which on-line stores offer the best price for a typical product. More specific, Shopbots [Kephart and Greenwald, 2002] are Internet agents that automatically search for information pertaining to the price and quality of goods and services. They do not sell goods, but guide the customer to recommended merchant’s on-line stores, offering these items. This recommendation can be based on the price only, or by taking into account multiple objectives [Keeney and Raiffa, 1993] (quality of product, delivery times and costs, promotions, ...) to rate a store for a typical type of product.

Instead of consulting all available on-line stores at the time a user requests information, we will use an system that learns this information, using artificial intelligence [Greenwald and Kephart, 1999]. Thus, after a training time, this learning system constructs a hypothesis, that could then be consulted to determine which on-line shops are most likely to offer low prices for desired products of the user, without scanning all possible websites at that time.

Such a system might improve its performance as measured by its ability to classify stores and product types correctly, through experience obtained, by examining and training itself on a large dataset of scanned websites, with specific store, product and price information. This idea is put into application by Doorenbos et al. [Doorenbos et al., 1997], where a combination of heuristic search, pattern matching, and inductive learning techniques are used to create an intelligent ShopBot system. Thus,

- Task T: classifying on-line stores and shops
- Performance measure P: price obtained for the desired product on the highest recommended store
- Training experience E: a database of scanned websites of on-line stores
In the literature, this is called a learning problem.

When one is faced with such a problem and wants to solve it, a learning system would have to be designed. This learning system specifies, next to the task, performance and training experience, other important criteria that will heavily influence the final learning behaviour of the system. Designing a good learning system, consists of determining what will be learned, how training experience will be presented and rated and what algorithm will be used in the end to construct an accurate model of the task. This involves reflections on the type of feedback information; is it direct or indirect? Meaning, do we immediately retrieve the effect of an action or not? In the example of the ShopBot, the feedback will be direct; the price offered on the website is available and used as feedback to learn from. But in other cases, this can be less trivial, for example, in the case of playing chess, it is much harder to determine the value of a certain move. Only at the end of the game, one can determine if it lead to success or not. Credit assignment can be a particularly difficult problem because the game can be lost even when early moves are optimal, if these are followed later by poor moves. Hence, learning from direct training feedback is typically easier than learning from indirect feedback.

Another question we need to ask ourselves is the definition of the target function, which states what we want to learn, but not how we want to do it. The target function is a function that needs to provide a mapping from an on-line store to a probability of recommendation of each available product type and we represent it by $V$.

$$ V : \text{Online store} \rightarrow \text{Product} \times \mathbb{R} $$

Such a function is too vague to be build into a learning algorithm to perform the job in practice. Therefore, one needs to find a representation of this target function that the learning program will use to describe the function that it will learn. This can be done for example by using an rule-based system, statistics or an artificial neural network, etc. This learning program will search for features in the products, offered by the stores, that it can use to make its decision on what store will most likely offer the best price for a given product. As already mentioned, an intelligent ShopBot could take into account more than only the price offered, but also other criteria such as delivery times and costs and much more. Thus we recall that a learning system consists of:

- Task T: What you want to do
- Performance measure P: How will you measure success
- Training experience E: A history of previously gathered examples
- Target function: Mathematical formulation of what should be learned
• Target function representation: Practical approximation or interpretation of target function

• Choice of learning program: Technique used to learn
1.8 Personal contributions

In our work, we have used the technical concepts, such as machine learning and learning systems, to investigate a new idea in SCM, involving a 4PL and an auction house, this, to tackle the work of Robu [Robu et al., 2008, Robu et al., 2005] and present other techniques to come to a price agreement amongst different stakeholders for transportation activities. The contributions of this research are summarized as follows:

- We provide a theoretical overview of supply-chain management in economics and all stakeholders involved, together with a survey of latest and state of the art ideas in these fields.
- The relation between supply-chain management, computer science and especially artificial intelligence is investigated. We study the possibilities of connecting these principles that at first sight might have nothing to do with each other.
- The DiCoMas simulator tool, used in this thesis, has been enhanced to simulate the new idea in SCM to combine both 4PL and an auction house to distribute transportation requests from manufacturers to carriers. In this tool, the performance and efficiency of this new setting can be examined and compared.
- We evaluate the performance of different algorithms and learning techniques of artificial intelligence in the field of SCM for cost optimisation and present experimental results.
- We provide guidelines on the choice of learning techniques and bundling algorithm for different settings and the trade-offs between them.
- A number of possibilities for future research is presented.

1.9 Chapter’s summary

In this first section, we have presented the background of this thesis, together with the main stakeholders and concepts behind it. We remember the different actors in the economical cooperation; meaning the manufacturers that create the goods and rely on transport companies (3PL) to pick-up and deliver their parts in time at the correct location. This, as parts are being assembled into a final product at different locations, before it is ready to be sold to individuals. Nowadays, long-term contracts are still used to define this cooperation between customers and
carriers, but as we have stated in section 1.1.4, these contracts sometimes do not fit both the customer and the 3PL company involved. As transportation needs became even more complex, another type of logistics company started to appear that solely focuses on orchestrating and coordinating the supply-chain. This is called the fourth-party logistics provider (4PL). Our research objectives consist of proposing a behaviour for the 4PL to increase flexible and dynamic price settings. In this thesis, we will examine the opportunities and effects of combining bundling behaviour with an auction house.
Chapter 2

Implementation study

In the previous chapters, we have focused on the background of supply-chain management and previous work done in this setting. In the following chapters, we will describe our study and contributions. Our ideas and techniques will be presented and how they reinforce each other to extract knowledge and features of the 3PL companies involved. This information can on its turn be used to bundle to reduce costs and expenses. Recall from the research objectives (1.6), that the main task of our work consists of two tasks. For starters, a reward function has to be learned, based on a history of bundled items, to extract or deduct the preferences of the 3PLs. This work is further explained in chapter 3. Furthermore, techniques should be introduced to use the information learned to actually form the bundles. The specification of the bundling system is presented in chapter 4.

Before we can start explaining the details of our techniques, we will first briefly cover the project this work is involved in and a proposed design to incorporate the two tasks of the 4PL in the project. This will provide the reader a first glance at the techniques used and how they collaborate.

2.1 DiCoMas project

The DiCoMas\(^1\) (Distributed Collaboration using Multi-Agent System Architectures) project is a SBO\(^2\) project funded by IWT\(^3\), running from 2008 until 2011. The long-term goal of this project is to establish a knowledge based platform on distributed collaboration in Flanders, Belgium. The concrete objective of the project consists of providing a reusable software architecture that supports the development of applications for automated collaboration between business pro-

\(^{1}\)http://distrinet.cs.kuleuven.be/projects/dicomas/
\(^{2}\)Strategic Basic Research
\(^{3}\)Instituut voor de Aanmoediging van Innovatie door Wetenschap & Technologie in Vlaanderen
cesses. DiCoMas project brings together the expertise in Multi-Agent systems, along with an international environment and aims to advance its complementary know-how on distributed collaboration, and to provide a valuable platform for knowledge transfer and valorisation. DiCoMas is focused towards collaborative business processes, such as supply chain management and collaborative health care institutions. Supply chain management focuses heavily on collaboration with customers and suppliers to establish and manage an effective supply network.

Researchers from different labs, all over the country, have been collaborating to implement a simulator capable of modeling the participants of the supply-chain and created protocols to make them work together. For example, carriers are present and enriched with their own PDP solver. Together with an auction house, capable of organise a bidding contest amongst these carriers. Our contributions are also be situated in this context, where we extend the simulator with a 4PL component, capable of bundling rationally, by learning the preferences of the carriers.

2.1.1 Previous work

Previous work in the simulator on the behaviour of the 4PL is limited and requires additional work. In a first stage, an attempt has been made by researchers from the CoMo lab\textsuperscript{4} to specify learning and bundling behaviour. The idea behind their work consists of dividing the world of customers into equally-sized grids and record bidding behaviour of the 3PLs in the auction house. This idea is presented in figure 2.1. The researchers provided a base for an on-line learning system, based on reinforcement learning (section 3.1.5) and statistics. This learning system tries to learn which regions are more promising than others. Therefore a reward system has to be constructed that can define a reward, between 0 and 1, on a bundle that was auctioned. These rewards will be calculated, only relying on the minimal feedback information from the auction house to the 4PL, as denoted in section 1.5. In their work, they used the following rules to calculate the reward of a bundle. In section 3.3, we use this work as a base for our contributions.

- Computation of the reward - to compute the reward of a bundle, several aspects of the bidding information are from the auction house are computed. These are:
  - Bids normalisation as rewards represent probabilities
  - The number of request in the bundle, \#requests to reward high quantity bundles

\textsuperscript{4}Computational Modeling lab
The smallest, winning bid, \textit{win\_bid} in the auction house on the bundle

The final rule consists of the statistical measures above, enriched with user-defined weights.

\begin{equation}
    \text{reward} = \text{Weight}_a \times (1 - \text{win\_bid}) + \text{Weight}_b \times \#\_\text{requests}; \quad (2.1)
\end{equation}

\begin{itemize}
    \item The researchers used the following weights:
        \begin{itemize}
            \item \text{Weight}_a = 0.8
            \item \text{Weight}_b = 0.2
        \end{itemize}
    \item Update the reward - to update the reward we have to define how to relate the new reward to an already existing reward. When a previously calculated reward is not available in the system, the new bundle’s reward is stored. The update rule is based on the Q-learning algorithm [Sutton and Barto, 1998]. When one updates a previously calculated reward with a new reward, the following update rule is used:
        \begin{equation}
            \text{new reward} = (1 - \text{lr}) \times \text{reward}_{old} + \text{lr} \times \text{reward}_{new} \quad (2.2)
        \end{equation}
\end{itemize}

More information on the statistical learning system can be found in section 13. In figure 2.2, we can see the effect of applying the learning system to the same world.
of customers, as in figure 2.1. A grid of 5x5 cells has been created to divide the world into equally sized areas. Based on a series of bundles and their value or the price 3PLs bid in the auction house, the learning program assigns rewards to areas based on bidding information. The higher this reward, the more interesting these grids seem to bundle future requests into and the higher their colour intensity. As we see in figure 2.2, two carriers were present, each represented by their depot (the red dot) located in the bottom-left and top-right corner of the grid. Based on the acquired information and the learning factor, the grids close to the two depots are assigned a higher reward than the areas located near the middle of the world. This result can be explained by the fact that the distance the trucks of the carrier companies have to cover (and return to the 3PL’s depot) is much smaller when the trucks have to pick-up and deliver requests in an area close to the home-depot. The further the pick-up and delivery requests are located from the starting location, the more the ground will have to be covered and the possible amount of empty kilometers can also be significantly larger in these areas. It is important to notice that this behaviour was learned by statistical learning rules and no rules were added manually to favour certain areas on the grid. More information on actual

Figure 2.2: A visual representation of the learnt grid preferences of the 3PL companies involved of problem instance LC1101 of the Li and Lim benchmark.

results on the performance of this learning system, using equally-sized grids, can be found in chapter 5. Our contributions consist of elaborating this work and propose other learning systems that take into account more aspect of bundles to calculate a certain reward. These systems are explained in chapter 3.
2.2 Design overview

As we recall, the objectives of the 4PL consist of two main tasks, meaning learning and bundling. The learning part will construct a reward function, that can later be used as a guidance to create bundles of transportation request that are complementary to each other. These two tasks are independent of each other and therefore, we propose to separate the learning from the bundling system, as presented in figure 2.3. The idea of decoupling the behaviour into two individual systems is further elaborated in chapter 3 and 4. Figure 2.4 elaborates figure 2.3 by adding more specific systems.
Figure 2.4: By decoupling the learning and the bundling, it becomes more convenient to change the behaviour of each system. Offering alternatives for learning and bundling techniques becomes much more easy.
In the following chapters, we will dig deeper into each component. In chapter 3, we will introduce the Reward Systems component, where two different ways are inspected to compute a reward function out of training examples. These two systems use a statistical and a neural network learning method, respectively. In chapter 4, we will focus on the bundling system and different ideas on how the reward function can guide the search towards attractive bundles. In more detail, a so called Transportation Request bundler is presented.

2.3 Benchmarks

One of the problems we are faced with is the lack of benchmark problems, concerning the world of 3PL and 4PL companies. Despite having contacted several logistics companies such as Ewals Cargo Care\(^5\) and Accenture\(^6\), to demand for real-life data on transportation activities, we did not receive any data. In an ideal case, we could compare the prices they received to the idea proposed in this thesis. The companies, on their turn, could learn a great deal on alternative price-negotiation techniques and therefore, it is a pity that we never received any data to compare our research to a real-world setting. This would significantly have influenced the industrial value of this thesis.

As an alternative, the Li and Lim [Li and Lim, 2001] dataset was proposed. This dataset consists of limited sets of PDP requests, covering 100, 200, 400, 600, 800 and 1000 customer locations. Each of this set then proposes a series of problem instances that are generated either randomly or clustered. Clustered data is more likely to represent real life situations, representing industry sites with enterprises located close to each other. This is artificial data, with no correspondence to real-world instances or real-life data. Therefore, these toy examples are useful for testing purposes in the simulator, but it is not fully scalable to a real-world setting.

2.4 Chapter’s summary

In this chapter, we have introduced the implementation study of the thesis. For starters, the simulation framework, provided by the DiCoMas project has been presented, together with our idea of decoupling the 4PL into two individual systems.

Furthermore, the benchmark issues and the lack of real-life data have been defined. As a result, we have to focus on the artificial Li and Lim benchmark.

\(^5\)http://www.ewals.com
\(^6\)http://www.accenture.com/us-en/industry/Pages/index.aspx
Chapter 3

Reward systems

In this chapter, we will focus on different ideas on how a reward function on 3PL’s bundling preferences can be constructed. The reward system represents a crucial part of the overall system as it is used to deduct 3PL’s bundling preferences. Other information on the 3PLs is not public, like for example the capacity and costs of the trucks, as presented in section 1.5.1.

In the following sections, we will explain how one can extract specific preferences of the 3PL companies, only based on the bids they arranged in the auction house. Several statistical measures and machine learning techniques are used to come up with a qualitative measure, representing the interest of the carriers. Figure 3.1 zooms in on the general overview of section 2.2, to present the contents of the current chapter.

Figure 3.1: In chapter 3, we elaborate on the Reward Systems.
More precisely, we present two approaches, using on-line and off-line learning methods, presented in section 3.1.1 and 3.1.2 respectively. These categories are further subdivided into supervised and unsupervised learning, based on the manner how feedback information is presented. These subdivisions in artificial intelligence and learning will be explained on the way. The application of these methods to the field of transportation is further presented in section 3.2 and 3.3.

3.1 Learning types

Before, we will start explaining our ideas on using on-line and off-line learning methods, it might be convenient to briefly present these two different learning methods. On-line and off-line learning methods will be explained, together with three different types of methods, used to describe the use of rewards in learning systems. These methods are supervised, unsupervised and reinforcement learning, respectively.

3.1.1 On-line learning

A first learning method we will present is on-line learning. In on-line learning, a model of induction is used, that learns one instance at a time [Vovk et al., 2005]. This is useful in situations where not all input data is available a priori. These algorithms have been used to compute new hypotheses incrementally as soon as a teacher provides new training examples. Because it does not know the whole input, an on-line algorithm is forced to make decisions that may later turn out not to be optimal. In general, a on-line algorithm consists of a sequence of three stages:

1. Receive the instance
2. Predict the value corresponding to the instance, this is called the (target) label of the instance
3. Optionally receive the correct or original label from the teacher and adjust your hypothesis on the way by comparing the actual label with the original label

The third stage is optional, as depending on the fact if the teacher provides supervised (section 3.1.3) or unsupervised (3.1.4) feedback.

In this project, we will use an on-line algorithm to construct an hypothesis that learns which characteristics of bundles truly define the cost of the bundle. As the cost depends on several criteria that are not published and the 3PLs’ behaviour in
the auction house is not deterministic, the learner has to deal with a lot of noise. The goal of the algorithm is to learn at the end of the day which criteria have the highest influence in the calculation of the bid and how one can exploit this knowledge to reduce the cost.

### 3.1.2 Off-line learning

Where in on-line learning training data is presented one at the time without having the entire input available from the start, in off-line learning the whole training data is available from the beginning. For a particular training time, a model will be constructed, based on all training data. This target function can then be used to test unseen examples, but it will not update its model anymore. That is the reason why off-line learners are typically more robust to noise than on-line learners. In short, an off-line learning system will first process all input data, before expressing its hypothesis. The construction of an off-line learning algorithm usually consists of a long training time, involving thousands of iterations, but in the testing phase the algorithm can be very fast as the hypothesis is static from that moment on.

In this thesis, we will examine the possibilities of off-line learning to achieve the same goal as expressed in section 3.1.1. But this time, a phase of data collection on previously bundled items and their characteristics will have to be constructed. Based on this training set, the off-line learner will attempt to create its hypothesis.

### 3.1.3 Supervised learning

In supervised learning, the training set consists of pairs input object and original label. The input object is used by the learner to create its hypothesis and the original label represents the desired output, we would like to receive out of the input object. Based on the training data, the (on-line or off-line) learner constructs a model of the data, represented by a function based on inference. The learner can then use this function to map a classification label on an input example and by comparing it with the original label, its model can be adjusted to better fit the data. The learner needs to generalise from the available training examples and be applicable to unseen instances, called the test data. In short, in supervised learning, next to the problem instance, also the solution is provided to the solver. The solver will then use both data to adjust its hypothesis and cover unseen examples better.

In the literature, several supervised learning algorithms are available, each with its strengths and weaknesses. Examples are backpropagation in artificial neural networks and the Naïve Bayes classifier.
3.1.4 Unsupervised learning

Compared to supervised learning, the teacher now does not provide a pair of input and desired output data, but only input data is available. The goal for the learner is to come up with an organisation of the data. In computer science, the relatively new field of *data mining*, heavily relies on unsupervised learning, to extract patterns and organisations from large training sets. Methods from the area of artificial intelligence and statistics are used and combined with database management to extract information from these large quantities of data [Fayyad et al., 1996]. Examples are cluster analysis and regression, where one attempts to create function which models the data with the least error. In unsupervised learning, only the problem instance is provided to the learner. The learner, on its turn, has to organise the data in such a way to construct a solution.

3.1.5 Reinforcement learning

Reinforcement learning is an area of machine learning, concerned which actions an agent is supposed to take in an environment, to maximize some notion of cumulative reward [Sutton and Barto, 1998]. This environment might be changing and evolving all the time and the optimal action to take in each state of the environment is not a trivial task. In contrast to supervised learning, where the correct and desired output is provided, this is not the case in reinforcement learning. In this learning technique, rewards are assigned to actions. The algorithm’s goal is to learn which actions are the best to take and which are not, hence, based on the cumulative rewards.

Also in the case of the 4PL, the desired output or original labels are not available and should be approximated by rewards. We will use reinforcement learning in the learning methods of the following section to determine which actions, representing different types of bundle criteria to take into account while bundling, are the best. This to gain the maximum reward possible over time.
3.2 On-line learning system

The first learning method, we present is based on an on-line, unsupervised learning method. Remember that in our setting, the goal is to search for inexpensive combinations of transportation requests that can be formed into a bundle. When the bundle is inexpensive for the 3PL company, a low price or bid will also be entered in the auction house. As we are building an on-line algorithm, in general, the results from initial runs will be poor as the model needs some iterations to adapt to the situation and construct its hypothesis. After a few trials, enough information is available to learn from and the performance will eventually increase.

In the following sections, we will present in detail our contributions on how to learn preferences using an on-line learning technique. We constructed a knowledge base, consisting of three properties. These properties are location, distance and volume characteristics, as presented in figure 3.2. Location is an important criteria of a bundle, as dividing the world into regions can provide information on so-called fruitful areas. These fruitful areas contain a high variety of other transportation requests in the neighborhood, and make it easier to find complementary requests that can reduce the total distance to be covered, specified in the bundle. Distance criteria also represent a significant part of a transport company’s costs, as some carriers specify a maximum threshold and once this restriction has been breached, its costs increase exponentially. Then, possibly, sleeping accommodation needs to be arranged when the truck driver can not return home at the end of the day. Recording a bundle’s volume is interesting to deduct capacity information of the trucks. This information can be used to construct bundles up to this threshold and not beyond it, as then, the bidder would have to arrange multiple trucks for the same bundle which increases the costs, of course.

![Figure 3.2: We will now focus on the on-line learning method.](image-url)
3.2.1 Cluster-based LS

Our first learning system’s goal consist of deducting location-based information. In real life, transport companies or industry in general are not randomly distributed across a country or region and government laws are there to restrict industrial companies to appear everywhere. Therefore, industry areas were introduced to reserve certain locations for industrial activities. In Flanders, Belgium, the agency for spatial planning\(^1\) performs the enforcement of these laws and distributes plans, denoting which activities (living, agricultural, industrial, etc.) can be performed on what geographical locations. Figure 3.3 represents the areas of industrial activities in Flanders. From the illustration, we can denote there exist regions with more industrial activities than others. Thus, in a practical setting, there is need for another approach than simply dividing the grid into equally-sized cells, as other researchers proposed in section 2.1.1. In artificial intelligence, techniques exist to arrange a certain amount of items into groups with similar characteristics, this is called \textit{clustering}. Clustering data is a form of unsupervised learning [Duda et al., 2001], which represents a class of problems in machine learning where the goal is to determine how data is organized. Many methods employed here are based on data mining. One of these clustering algorithms is \textit{K-Means}, we will look into it in more detail in the following paragraph.

\(^1\)Agentschap voor Ruimtelijke Ordening, http://www.ruimtelijkeordening.be/

Figure 3.3: In practice, industrial activities are not distributed randomly, but are assigned certain locations where this activity can be performed. These areas are called industrial zones. Source: AGIV, Agentschap voor Geografische Informatie Vlaanderen
K-Means

The K-Means algorithm, first presented by Hartigan [Hartigan and Wong, 1979], is an unsupervised learning algorithm that solves the clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (denoted by the $k$ parameter) fixed a priori. The procedure starts of by initialising $k$ centroids, which is the center of a cluster and represents the average of all the points in the cluster. Often, the initialisation of the clusters is done in a random fashion. For each data point, we then calculate its closest centroid and we assign it the corresponding label. This is iterated until no points are swapped between clusters (their label remains unchanged) and convergence is achieved. Figure 3.4 presents the K-Means algorithm using a flow-chart.

![Flow-chart of the K-Means algorithm](image)

Figure 3.4: The different steps in the K-Means algorithm, expressed using a flow-chart.

To calculate the distance between points, a distance measure is needed. This will determine how the similarity of two elements is calculated and will influence the shape of the clusters, as some elements may be close to one another according to one distance and farther away according to another. In the literature, several distance measures are proposed:

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• Euclidean distance - The mostly used distance measure, based on the Pythagorean formula.

\[ d(X,Y) = \sqrt{\sum (X_i - Y_i)^2} \]  \hfill (3.1)

• Manhattan distance - or Taxicab geometry is a metric in which the distance between two points is the sum of the absolute differences of their coordinates

\[ d(X,Y) = \sum_{i=1}^{n} |X_i - Y_i| \]  \hfill (3.2)

In our learning system, we also relied on the Euclidean distance metric as it is widely used. In pseudo-code, the algorithm looks as follows:

```plaintext
input : X: a set of N data vectors
        C_i: initialised k cluster centroids
        C: the cluster centroids of k-clustering
        P = {p(i) | i = 1...N} is the cluster label of X
output: A partitioning of the data into k groups

1 Loop until convergence;
2 while C ≠ C_{previous} do
3     C_{previous} ← C_i;
4     Cover all data;
5     for i ← 1 to N do
6         Calculate new labels;
7         p(i) ← \arg \min_{j<k} \text{Distance}(x_i, C_j);
8     end
9     Calculate new centroids;
10    for j ← 1 to K do
11       C_j ← Average (∀x_i ∈ X, where p(i) = j);
12    end
13 end
```

**Algorithm 1:** Outline of the K-Means algorithm

K-Means is a greedy algorithm for partitioning the n samples into k clusters so as to minimize the sum of the squared distances to the cluster centers. It does have some weaknesses:

• The way to initialize the means was not specified. One popular idea that we also applied is to randomly choose k of the samples.

• The results are heavily influenced by the distance measure used.

• The results depend on the value of k.
This last problem is particularly troublesome, since we often have no way of knowing how many clusters exist. At the moment, there is no general theoretical solution in the literature to find the optimal number of clusters for any given data set. The k-parameter should not be set blindly, but in accordance of the available data and the way it is organised. Nevertheless, the algorithm provides some strengths as it always converges to a local optimum and is fast for most applications. Therefore, it is also applicable for our setting, where we want to cluster the pick-up and delivery locations of our benchmark instances.

We used the K-Means algorithm to divide the 1000 locations, presented by their pick-up and delivery coordinates into cells, based on their density. 25 clusters were used, this based on an experimental evaluation of the resulting clusters with different values for the k-parameter. Illustrated by figure 3.5, on the left hand side, we see the different locations, where on the right hand side, the clustering technique is used to discretise the world into 25 cells with similar density. To visually represent the clusters, Voronoi [Aurenhammer, 1991] diagrams were used.

![Figure 3.5: The K-Means algorithm applied to the world of pick-up and delivery locations of instance LC1101 of the Li and Lim benchmark and visually presented by Voronoi diagrams.](image)

The learning method

After the discretisation of the world into cells (clusters), a learning method was applied to learn which cells are of a high concern to the 3PLs. The goal is that the bundler of section 4 can take advantage of this knowledge and combine areas with a high matter of interest with regions with lower importance, to in the end make sure all items can be shipped by the 3PL companies and a fair price is obtained.
One of the major problems, we were faced with while constructing the cluster-based learning system, was the fact that transportation bundles are filled with transportation requests, covering multiple cells on the map. For example, figure 3.6 visualises a bundle X, covering cells $[1, 2, 3]$ is auctioned off for price $Y$. One of the questions was how to distribute rewards to a combination of regions.

![Figure 3.6: Visualisation of bundle X with 4 PDP requests, covering 3 cells. Departure and destination locations are presented in white and black dots, respectively.](image)

One could extract the individual cells, $[1]$, $[2]$ and $[3]$ and distribute the reward over these cells individually. This would be a naïve idea, as in most cases, the bid placed on a bundle, reflects the value of the entire bundle to the 3PL. Because an intelligent bundler knows that at the end of the day each transport item should be auctioned off to a carrier, it could combine transport items, covering less attractive cells, with items, located in interesting regions. Thus, obtaining a good price. When one would learn the rewards for each cells individually, less information on the locations can be extracted and will be lost, as there is no clear distinction anymore between good and bad regions.

Therefore, we propose to learn the rewards for the combinations of regions and to create a knowledge base recording the rewards for every cell and combination of cells presented to the learner. In the previous example, rewards are learned for all covered cells, meaning $[1, 2, 3]$ and combinations with other cells, like $[1, 2, 3, 4]$
To conclude, the formulation of the cluster-based learning system is specified as follows:

- **Task T**: The goal is to extract location-specific preferences of all carrier companies involved
- **Performance measure P**: Success is rated by the bid carriers place on bundles
- **Training experience E**: A history of previously bundled items
- **Target function**: \( V : \text{Bundle} \rightarrow \mathbb{R}^+ \)
- **Target function representation**: Assign a credit or reward to bundles, based on the clusters they cover, in accordance to the bids in the auction house
- **Choice of learning program**: Statistical learning system

### Statistical learning system

A statistical learning system was conducted to assign reward onto bundles. The major details such as the reward calculation and update rule of this learning system will now be examined.

- **Computation of the reward** - to compute the reward of a bundle, several aspects of the bidding information are from the auction house are computed. These are:
  
  - **Bids normalisation** - As rewards depict probabilities between 0 and 1, normalising the bids is needed.
  - **The number of requests in the bundle, \#requests** - Recording the number of requests in a bundle is included in the learning rule to reward the bundling system of the 4PL. If the 4PL attempts to bundle and group multiple items together instead of creating single-item bundles, this will be reflected in this metric.
  - **The winning bid, win_bid** - The winning bid represents the best price provided by the 3PLs.
  - **Compute the average bid, avg_bid** - The average bid provides information on the degree of interest of all 3PL companies involved in the bidding process.
Compute the standard deviation of the bids, \( std_{\text{dev}} \text{bid} \) - The standard deviation provides information on the degree of variance in the different bids.

The learning rule is as follows:

\[
\text{reward} = \text{Weight}_a \times (1 - \text{win}_{\text{bid}}) + \text{Weight}_b \times \#\text{requests} + \text{Weight}_c \times (1 - \text{avg}_{\text{bid}}) + \text{Weight}_d \times (1 - \text{std}_{\text{dev}}\text{bid})
\]  

(3.3)

- These weights are empirically assigned and sum up to 1.
  - \( \text{Weight}_a = 0.6 \)
  - \( \text{Weight}_b = 0.2 \)
  - \( \text{Weight}_c = 0.1 \)
  - \( \text{Weight}_d = 0.1 \)

- Update the reward - to update the reward we have to define how to relate the new reward to an already existing reward. When a previously calculated reward is not available in the system, the new bundle’s reward is stored. The update rule is based on the Q-learning algorithm [Sutton and Barto, 1998]. When one updates a previously calculated reward with a new reward, the following update rule is used:

\[
\text{new reward} = (1 - lr) \times \text{reward}_{\text{old}} + lr \times \text{reward}_{\text{new}}
\]  

(3.4)

The learning rate or \( lr \) determines to what extent the newly acquired information will override the old information. A factor of 0 will make the agent not learn anything, while a factor of 1 would make the agent consider only the most recent information. In our experiments, we have set the learning rate to 0.1, to indicate that we want to learn gradually over time and adjust the hypothesis slowly, because of the vast amount of noise in the bidding information.

The statistical learning system presented above consist of several rules that combine extracted metrics from the bidding information, provided by the auction house. Using these rules, a knowledge base is constructed. It is important to notice that the definition of this learning system comprises 5 parameters (4 weights and 1 learning rule).

The result of the cluster-based learning system, is presented below. In figure 3.7, we applied a plotting technique, where promising regions are displayed in a higher intensity in colour. Two 3PLs are present, denoted by red dots, from
whom bundle preferences will be extracted and used to learn which clusters are more interesting than others. Based on this information, areas around the two depots seem to be receiving a higher reward than other clusters which are located further away from the base-stations of the two companies. This was one of the first, logical results achieved, where other types of location-based information could be extracted. As transport orders in clusters close to the depot require less fuel and time to be covered, these areas and their combinations are considered promising and fruitful and could be used in such a way to combine them with less interesting transport items to ensure a good price. Another way to present the same information, other than printing the locations, is to express the rewards associated with each cluster using a graph. In figure 3.8, we plotted the individual reward for each cluster, using a histogram. Also in this representation, cells located near the depots (left and right of the histogram) are given a higher reward, than cells at a larger distance, in the middle of the histogram. Therefore, the plot receives a saddle shape, with high values near the extremes. Clusters with a high intensity in figure 3.7, also have a high reward in this illustration, like for example cluster 18.
Figure 3.8: The graph above plots the individual rewards of each cluster after running it 100 simulation days. Some clusters are more promising than others and are denoted with a higher reward.

Results

The advantage of creating different learning systems that each focus on one bundle characteristic is that one can test the behaviour of the systems individually before combining it into one combined system. This allows the developer to tweak the performance of one learning system individually, regardless of the influence of other learning system. The figure below (3.9) uses the bundling method TRBS, explained in 4.1 on top of this cluster-based learning system to construct bundles that seem promising from the cluster-based LS’s point of view. We used a predefined experimental configuration, configuration 1 (A.1) which we will also use in our following experiments. In this experiment we use as performance metric the average price per kilometer for the 3PLs. As the goal of the algorithm consists of constructing interesting and cheaper bundles for these companies, the goal is to see the price per kilometer drop over time. Only relying on the cluster-based LS, we can deduce from graph 3.9 that in initial runs the algorithm is exploring different settings and the price per kilometer drops until a final performance of around 61 cost units is achieved. Because reports on learning and bundling systems for the 4PL is not covered in the literature, it is not convenient to compare our work with known benchmarks. In this stage, where the 4PL is a relatively
new concept, we can only compare our work to simple bundling schemes, such as random bundling, single-item bundling and no bundling at all. From the figure, we can depict that our learning method clearly beats those bundling schemes.

Figure 3.9: The graph in red presents the performance of the TRBS bundler (section 4.1), running on top of the cluster-based LS. After exploring different settings, the algorithm exploits its search towards promising bundles with a cost that is a little bit lower than using equally-sized grids. Performance on no bundling (all items auctioned off together), random bundling and single-item bundling is also present in green, purple and blue, respectively.

To conclude, we can say that the result achieved with the cluster-based LS is promising for future results. Not only because we receive significantly good results in the simulator using an artificial benchmark, but also because we have proven the practical value of using a clustering algorithm in the model.
3.2.2 Distance-based LS

In addition to a cluster-based learning system, one could also take into account the distances between the pick-up and delivery locations in a bundle. The distance plays an important step in the calculation of the expenses and thus also implies a significant part of the bidding strategy of the 3PL company. On the 3PL’s side, a PDP solver is used to search for (close to) optimal tours between pick-up and delivery locations, to reduce the cost and fuel necessary. Starting from the depot, several route combinations are examined and the best one is recorded and used in the GPS\textsuperscript{2} of their truck drivers.

Distance is an important aspect of bundles, because the distance between location directly influences the fuel consumption of the trucks used in the process. If this distance exceeds the number of kilometers a truck can cover with a full fuel tank, it will have to refuel in one of the commercial fuel stations along the road, instead of using the local petrol station, located at the 3PL’s site, which is of course much cheaper. In some cases, the trucks will have to refuel using the commercial stations, or even return to the depot to refuel, but the goal is to limit these actions and ensure no unnecessary kilometers are traveled.

The learning method

The goal of the learning system we will present next, is to take into account this constraint and learn aspects of the 3PLs preferences on distance criteria. In section 4, the bundling system will use this information as a guidance to bundle transportation request close to the best distance between the locations. A precise description of the learning system is given as follows:

- **Task T**: The goal is to extract distance-specific preferences of all carrier companies involved
- **Performance measure P**: Success is rated by the bid carriers place on bundles
- **Training experience E**: A history of previously bundled items
- **Target function**: \( V : \text{Bundle} \rightarrow \mathbb{R}^+ \)
- **Target function representation**: Assign a credit or reward to bundles, based on the distances needed to cover between PDP locations, in accordance to the bids in the auction house
- **Choice of learning program**: Statistical learning system

\textsuperscript{2}Global Positioning System
The final three specifications of the learning system, meaning, target function, target function representation and choice of learning system and presented in depth in section 13, where a similar learning system is presented for the cluster-based LS, with similarities to the underlying learning program of this system. The definition of the reward calculation in the statistical learning system was general enough to be applied for this learning system also.

Using a PDP-solver, we could estimate the behaviour of the 3PL’s PDP and examine if there exists a correlation between the distances and the prices offered. But as mentioned in section 1.5.1, the location of the depot of each 3PL company is not known and the 4PL has no knowledge about its coordinates. If this would be the case, the 4PL could rather easily bundle items close to each depot, and these bundles would contain excellent distance characteristics.

Therefore, another idea should be used to represent the location of the depot. One could propose to use a single, random, fixed point, and use it to denote it as a depot-location. But this is far from an ideal solution as we are constructing a model of the behaviour of multiple 3PL companies and examine their bidding behaviour, in the presence of other 3PL companies in the auction house. To accommodate to these shortcomings, we propose another idea: To determine if a bundle is competitive on the distance-criteria, we propose to plot the pick-up and delivery locations and use the geographical center point as the depot location. In figure 3.10, we illustrate this idea by denoting pick-up and delivery location by small boxes. The solid arrows show the direction of the request and the dotted lines reflect on the added distance, meaning the distance to travel from and to the depot. In the learning systems, rewards are assigned to the total distance, covered by all arrows involved in figure 3.10.

At first sight, the idea that we calculate the sum of the distances, represented by the arrows, might seem naïve, but is in fact a simple solution to map a number, representing the distance, to a bundle of transport items. Because it is that simple, the computational effort of calculating this number is reduced to a minimum. In an ideal case, not taking into account the computational effort, a shortest path algorithm, such as the Dijkstra algorithm [Dijkstra, 1959] could be used to extract the shortest path and solve the TSP\(^3\) between all nodes of the PDP requests. But due to the fact that this learning system is used in an on-line fashion, the impact of running this algorithm on the total running time would become too large.

Figure 3.11 uses a graph to represent the information learned, concerning the ideal distances between PDP locations. As distances are of a continuous matter, we applied a discretisation method, where rewards are learned for every multiple of 50 distance units. The underlying statistical model is the same as specified in section 13. From experimental results, we can conduct that smaller distances

---

\(^3\)Traveling Salesman Problem
Figure 3.10: The location of the depot is introduced as the center point between all PDP requests.

between these locations receive higher rewards than large distances, as in fact logical. The closer the PDP locations of transport items in a bundle, the less time and fuel is used to cover them.

Results

As before, it might seem interesting to look into more detail on the performance of this reward system individually. We used the same settings as in the previous experiments, meaning configuration I (A.1). Denote that in figure 3.12, the performance is not great, a final cost of 73 units is achieved where in earlier learning systems, we were able to reach better performance.
Figure 3.11: Distances between the PDP-locations and the depot are examined and stored to construct a reward function.

Nevertheless, we believe that taking into account a distance criteria is an important aspect of real-life transportation and therefore a true bundler should take this information into account. Remember that the benchmark we are using is not totally applicable to the scene of 4PLs and bundling. This could be one of the reasons why this system lacks the ability to reach similar performance as explained before.
Figure 3.12: The graph in red presents the performance of the TRBS bundler, running on top of the distance-based LS. After exploring different settings, the algorithm exploits its search towards promising bundles with a final performance of cost of around 73. Performance on no bundling (all items together auctioned off together), random bundling and single-item bundling is also present in green, purple and blue, respectively.

3.2.3 Volume-based LS

A third learning system that can help reinforce the knowledge on the 4PL side, is a system that tries to learn the capacity of the trucks of the 3PL. The capacity of the truck and the volume of the bundles heavily influences the amount of transportation equipment needed. The 3PLs do not own an unlimited amount of trucks, thus, filling the trucks to its maximum (and not beyond it) is a good strategy to keep into consideration while bundling. As already specified in section 1.5.1, information on the type of trucks used by every 3PL and their capacity is not available. Nevertheless, it is a crucial part in the calculation of the cost and therefore should not be overlooked. This is in fact the goal of this learning system, to learn preferred volumes for the carriers and use this information to bundle in accordance to what have been learned. We summarize:

- Task T: The goal is to extract volume-specific preferences of all carrier companies involved
• Performance measure P : Success is rated by the bid carriers place on bundles

• Training experience E : A history of previously bundled items

• Target function : \( V : \text{Bundle} \rightarrow \mathbb{R}^+ \)

• Target function representation : Assign a credit or reward to bundles, based on the volumes that need to be carried, in accordance to the bids in the auction house

• Choice of learning program : Statistical learning system

The final three specifications of the learning system, meaning, target function, target function representation and choice of learning system and presented in depth in section 13, where a similar learning system is presented for the cluster-based LS, with a lot of similarities of the underlying learning program of this system.

In figure 3.13, we see the result of applying the learning method on a series of previously bundled items and through a learning rule, rewards are assigned to discretised values, representing the volumes. In the simulator, homogeneous trucks are used with a fixed capacity of 100 units, which represents a Full Truck Load or FTL. Our goal is to bundle items up to the volume of 100 units or a multiple of this amount to ensure that the trucks used are filled close to their maximum. The output of the learning system, in figure 3.13, rewards are increasing up to this maximum amount, i.e. 100 units, afterwards the rewards are decreasing, meaning it is less interesting for the 4PL to bundle items with such large volume characteristics. From a volume of 200 units, the rewards are increasing a bit and it is clear that the algorithm is struggling to construct a clear hypothesis. This, because bundles with a volume higher than 200 are very rare in the system and not enough data is present for the system to learn correctly. Up to a volume of 150 units, enough data is present to learn correctly.
Figure 3.13: In the learning system, distances are recorded and rewards are assigned. Up to a volume of 100 units, the rewards are increasing as a FTL is almost reached, but beyond this threshold, the costs of arranging multiple trucks from one bundle become too large and the rewards drop significantly.

**Results**

Figure 3.14 denotes the performance of the volume-based algorithm individually. As we can see the algorithm is struggling to create optimal bundles and the final performance is not promising. Although the idea behind the volume-based LS is correct and real-life applications will for sure use the volume criteria while bundling, it does not seem an interesting criteria using the Li and Lim benchmark used in this experiment. Nevertheless, it still performs much better than the other bundling strategies, mentioned in the same figure. This is the reason, why we still use the information gained from the volume-based system in the overall or combined system, but with reduced importance.
Figure 3.14: The graph in red presents the performance of the TRBS bundler, running on top of the volume-based LS. We can see that the algorithm is struggling to find good bundles and is not able to explore the space of bundles good enough. Its final performance stops at around 110 cost units. Performance on no bundling (all items together auctioned off together), random bundling and single-item bundling is also present in green, purple and blue, respectively.

3.2.4 Combined system

In the previous sections, we have proposed three learning systems that each take into account one criteria of bundles. These criteria are:

1. The location on the grid, using a cluster method to divide the world into equally-dense regions
2. The distances between the pick-up and delivery locations in a bundle
3. The volume of a bundle

These learning systems build reward functions (figures 3.8, 3.11 and 3.13), able to distinguish between good and bad properties of bundles and can be used individually to group transport items into bundles and satisfy the criteria they aim to take into account. The goal now is to find a way to let these separate systems work together, in a multi-objective setting, to satisfy all criteria and generate bundles.
that are (close to) optimal when one observes it from different angles. Meaning that location, distance and volume criteria are met.

When a bundle is constructed, its properties are calculated for each of the learning systems individually. To get an overall judgment on the quality of the bundle and the price one can expect from the carrier companies, the three learning systems are consulted and assigned weights to obtain a single reward-value, indicating the quality, weighted over the three learning systems, each by their importance and influence in the overall price setting. In the simulator, these weights were assigned on an empirical manner. More precisely, after investigating the behaviour of the different learning systems individually, it was clear that some systems perform better than others and weights are assigned on this base. When we reflect on the definition of the research objectives of this thesis, we can now more precisely fill in rough schematic overview of figure 1.11. The three learning systems are combined by weights that reflect on their importance in the calculation of the price. Figure 3.15 depicts this behaviour in more detail.

Figure 3.15: Weights are used to combine the three learning systems, to get an overall judgment on how good a bundle is and what price we may expect to return from it.
Results

When one compares the performance of the three learning systems individually, in figure 3.9, 3.12 and 3.14 respectively, one can denote that the cluster-based LS is performing the best, followed by the distance and volume-based systems. The weights used for the combined learning or combined system is set to 0.6, 0.3 and 0.1 for the cluster, distance and volume system, respectively. The final performance of this setting is situated in figure 3.16. Recall that the three previous learning systems achieved a final performance of 61, 73 and 110, respectively. By combining them and tweaking the weights parameters manually over different runs, a significant better performance was achieved, resulting in 48 cost units. For more impressions and experimental results on the combination of learning systems, we refer to chapter 5.

Figure 3.16: The graph in red presents the performance of the TRBS bundler, running on top of a weighted combination of all LS. A final performance of 48 cost-units was achieved.
3.2.5 Conclusion

In the previous sections, we have presented three different learning systems that rely on statistics to extract preferences of bundles that are appealing to the 3PLs, involved in the auction house. The practical value of each learning system is examined individually. As we have seen, the performance of each algorithm is different, but in the combined system a weighted combination of each learning system was found, where the weights reflect the degree of importance of each learning system. This is the reason why the volume-based LS is not rejected, but given a low weight in the calculation of the combined hypothesis. Although the fact that for example, the volume-based system is not performing optimally and perhaps even better results could be achieved by simply deleting this system, we did not chose to do so. This, because in a practical setting, with real-world data and benchmarks, it is possible that the volume-based system is performing very good in those circumstances. Rejecting learning systems that do not perform ideally, although their existence is justified, is according to us, negative for the future work of this thesis.
3.3 Off-line learning system

After describing the idea behind off-line learning, in section 3.1.2, we can now explain in detail the type of learning algorithm that was chosen and why. Remember that off-line learner is interesting for learning a target function out of a series of input data with noise. Previous studies on artificial neural network found out that it is very applicable to map input to a desired output in a noisy setting. In our case, the input consists of features of bundles and the output reflects on the bids of the auction house. Before we further go into the subtleties on the reward calculation, let us first discuss the learning method into detail. Figure 3.17 present the contents of the current chapter, by zooming-in from the bigger figure in 3.

![Diagram of Reward System]

Figure 3.17: We will now focus on the off-line learning method, using neural networks.

3.3.1 Artificial neural networks

Neural network (or NN) learning methods provide a robust approach to approximating real-, discrete- and vector-valued target functions, like learning to interpret in a complex real-world sensor data artificial neural networks are among the most effective learning methods currently known [Duda et al., 2001]. There have been successful applications of neural networks to many practical problems such as learning to recognise handwritten characters [Lecun et al., 1989].

History

Neural networks inherit their name from the analogy with connections in the human brain. The human brain is estimated to contain a densely interconnected network of approximately $10^{11}$ neurons, each connected, on average, to $10^4$ others [Doszkocs, 1997]. These connections, represented in figure 3.18, called synapses,
are usually formed from axons to dendrites, though dendrodendritic microcircuits and other connections are possible. Using this network of neurons, humans are capable of making complex decisions, surprisingly fast. Researchers in the field of computer science adopted this idea to create a computational model that is inspired by the structure and functional aspects of these biological neural networks [Mitchell, 1997]. Such a neural network consists of an interconnected group of artificial neurons, that uses a mathematical model for processing information.

The model

It was stated that NN provided significant possibilities for solving artificial intelligence problems without necessarily creating a full model of a real biological system. The real, biological nervous system is highly complex: artificial neural network algorithms attempt to abstract this complexity and focus on what may hypothetically matter most from an information processing point of view. This model is depicted in figure 3.19, where a multilayer perceptron is presented. This is a feedforward NN model that maps sets of input data onto a set of appropriate output. Notice it is equipped with a hidden layer and transfer function $\sigma$, making the NN capable of learning on separating non-linearly separable data. This network has an input layer (on the left) with three neurons, one hidden layer (in the middle) with three neurons and an output layer (on the right) with three neurons. There is one neuron in the input layer for each predictor variable.

- **Input Layer** - A vector of predictor variable values ($x_1...x_p$), also called feature vector, is presented to the input layer. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the input

![Figure 1. Biological Neuron](image)

Figure 3.18: Artificial neural networks are inspired by neurons and their activities in the human brain. Source: [Doszkocs, 1997].
data, there is an additional input, called the bias that is fed to each of the hidden layers.

- **Hidden Layer** - Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight \((w_{ji})\), and the resulting weighted values are added together producing a combined value \(u_j\). The weighted sum \((u_j)\) is fed into a transfer function, \(\sigma\), which outputs a value \(h_j\). The outputs from the hidden layer are distributed to the output layer.

- **Output Layer** - Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight \((w_{kj})\), and the resulting weighted values are added together producing a combined value \(v_j\). The weighted sum \((v_j)\) is fed into a transfer function, \(\sigma\), which outputs a value \(y_k\). The \(y\) values are the outputs of the network.

**Backpropagation**

To make a neural network that performs some specific task, we must choose how the units are connected to one another (see figure 4.1), and we must set the weights on the connections appropriately. The connections determine whether it is possible for one unit to influence another. The weights specify the strength of the influence. We can teach a three-layer network to perform a particular task by using the following procedure:

1. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units.

2. We determine how closely the actual output of the network matches the desired output.
3. We change the weight of each connection so that the network produces a better approximation of the desired output.

In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. As the algorithm’s name implies, the errors propagate backwards from the output nodes to the inner nodes. The back propagation algorithm is the most widely used method for determining the EW. For more information on neural networks and backpropagation, we refer to [Mitchell, 1997], [Duda et al., 2001] and [Russell et al., 1996].

3.3.2 Application

After introducing ANNs, we will now focus on how to apply them in the context of the 4PL company. Although, there are still some unanswered questions on how to apply the NN in the scene of transportation and bundling transportation items. These questions will be answered right away.

Input layer

We first presented the different learning systems, which use statistics to learn on a bundle’s location, volume and distance. The goal is now to use a neural network to map a bundle on a reward and learn on the characteristics of successful bundles. Therefore, we could define in the input layer of the neural network three neurons that each represent the input data, representing location, volume and distance information. At first sight, this would seem an easy solution to the way rewards are calculated in the statistical learning system. Remember that in those systems, the one has to come up with a learning rule himself. Fine-tuning these parameters is not an easy task when the number of parameters is quite large to come up with good results. In that way, the neural network could to these calculations automatically, as it relies on the backpropagation algorithm, mentioned in section 3.3.1.

One problem that one is faced with is the location-based information. One could extract the names of the clusters transportation requests are situated into and also feed it into the NN. Several difficulties appear with this approach as these cluster number are not static, but generated almost randomly by the K-Means algorithm (section 3.2.1), therefore losing all of its information when one attempts to use this information in an off-line manner. Also, several questions on how to express combinations of clusters, also mentioned in 13, remain non-trivial. Hence,
we decided to restrict the neural network from using location-based information in its calculations and only rely on distance and volume characteristics of bundles, making the NN use only two neurons in the input layer. The input layer of the NN requires as many neurons as input data. Input data to lay in the interval [0, 1], consequently, we normalised the input data before feeding it into the network. It might be important to notice that we created this training set ourselves, by extracting volume and distance characteristics of bundles, created by the on-line approach.

**Hidden layer**

The ANN we chose, consists of a hidden layer to increase its expressive power. Recall that a NN without a hidden layer is only capable of solving linear separable problems. As we are aware of the fact that our input data consists of some noise, we focused on creating a robust NN and therefore added a hidden layer. A series of three neurons in the hidden layer was used.

**Output layer**

The output layer consists of one neuron representing the reward of the bundle. This reward should reflect on the price, taking into account that cheap bundles should receive the highest rewards. As we have obtained a training set of bundles, indicated by their volume and distance characteristics, as mentioned before, together with the bid obtained from the 3PL, we could simply use the normalised bid and use the following equation to express the original label:

\[
\text{True label} = 1.0 - B_{3PL}
\]  

(3.5)

\(B_{3PL}\) represents the winning bid of the 3PL company in our training set. The final configuration of the neural network looks like presented in figure 3.20.
Figure 3.20: The configuration of our network consists of two input neurons representing the (normalised) distance and volume information of the training set of bundles, a hidden layer with 3 neurons and one neuron in the output layer, representing the reward.

**Results**

After training the neural network on a dataset of 5831 bundles for 20,000 iterations, an average training error of 0.0201 was achieved. The figure 3.21 presents the absolute difference between 80 original and output labels of the NN, after it tested its hypothesis on the same data set used for training. As we can see, the difference between the two outcomes is minimal and close to zero, which means that there is a significant mapping and the NN was capable of learning.
Figure 3.21: The red histograms denote the absolute difference between the original and the target label on the training data. The maximum difference possible is 1, where in this case the difference is minimal and limited to 0.25.

Figure 3.22 displays the same type of information, but in this case, not the training data was used as input, but unseen data was used, collected from different runs. On this unseen data, we can see that the difference between the original and the output label is larger, but will not exceed a 0.35. If the difference between the original label and the one returned by the NN would be much larger, this would be a sign of overfitting. Overfitting is a serious problem in machine learning and data-mining, as the hypothesis learned is too specific, e.g. covering the training-set too much, and not general enough to be useful for any unseen examples. In that case, our outcomes are normal and the hypothesis is general enough to be applied on unseen examples.

The way a 3PL conducts its price is based on much more than these two properties, we take into account in this system. Nevertheless, we have seen in this experiment on artificial data, that a NN is capable of constructing a hypothesis that can be used to deduct preferences of 3PLs.
Figure 3.22: The red histograms denote the absolute difference between the original and the target label on testing data. The maximum difference possible is 1, where in this case the difference is limited to 0.35 which is acceptable.

When the NN is used as a knowledge base, exploring additional bundling schemes in the system is not necessary as the reward system is static and will not change. Therefore, we chose a boxplot representation to denote the performance of the NN reward system on the TRBS bundler (section 4.1). In figure 3.23, we ran this configuration 5 times and 5 different boxplots were used to denote the performance. Recall that the combination of LS in the combined system achieved a total performance of 48 cost units, in section 3.2.4. Using the NN, which uses in fact less information (e.g. only volume and distance criteria and not location-based information), even better performance was achieved, with means around 46 cost units and much less outliers than in the on-line system. A decrease of 4.1% is achieved compared to the on-line system.
After presenting the details and subtleties behind artificial neural networks, we have presented how one can use this system to deduce properties of desirable bundles. Through the sections, the benefit of using a NN to construct a knowledge base is justified. With a NN, the overview of the system is presented in figure 3.24. The performance of the NN system is quite remarkable. Remember that similar performance was achieved with the statistical learning system, where the greatest influence was given to the cluster-based system. On the other hand, in the NN system, the location-based (cluster) information was not used and it relied only on distance and volume criteria. Criteria for which we have denoted rather poor performance in experiments with the statistical learning system. Remarkably, the NN is capable of constructing an hypotheses that works quite well to extract more information, using less attributes. This could be the case, because the statistical learning system involves the tuning of several parameters, that greatly influence to overall performance. In total 15 parameters influence the three statistical learning systems and 3 weights are used in the combined system. This is not the case in the NN, where backpropagation is capable of tuning its weights in the neural network automatically. We believe this is the strength of the neural network in this setting.
3.4 Chapter’s summary

In this chapter, we have proposed and presented two ways of calculating the rewards of bundles. Rewards represent the value of a bundle, based on its properties. In a later stage, in chapter 4, these reward systems are used as a guidance to create bundles with similar properties as the ones which have been proven their value.

In a first reward system, rewards are calculated using a combination of several statistical measures, such as normalisation, standard deviation and mean. This learning system bases its knowledge on three criteria; location, volume and distance. Through sections 3.2, more information on these learning systems and how to combine them have been presented in detail. This system uses on-line learning, constructing a hypothesis from scratch, based on the current information present.

In an off-line setting, a neural network was used to construct a single hypothesis, which is general enough to be used on future bundles and benchmarks. This system only relies of distance and volume information for the reasons presented in 3.3.2. Nevertheless, we have proven a hypothesis was constructed, general enough to be used on unseen examples and specific enough to contain relevant information.
Chapter 4

Bundling mechanism

In this chapter, the bundling mechanism will be presented that relies on an accurate reward system to create bundles. More precisely, by keeping the information from the knowledge base in mind, this system will assign items into groups that are likely to produce good bids in the auction house. Hence, we present a bundling method that relies on A.I. techniques and balances between exploration and exploitation (section 4.1).

4.1 Transportation Request Bundling System

A first bundling system we propose, is called the Transportation Request Bundling System or TRBS. The idea behind this bundling algorithm comes from the fact that in the data collection phase a lot of noise is present which disturbs an accurate calculating. More precisely, not all parameters in the computation of the objective, e.g. the reward representing the value of a bundle, are known. As already mentioned in chapter 3, approximations, discretisations and assumptions were used in the construction of the knowledge base. Although we tried to take into account multiple bundle characteristics, such as volume, location and distance properties, we are aware of the fact that 3PLs use much more criteria in their calculations. Criteria that are not public (section 1.5.1), but having a significant influence. Bearing these assumptions and discretisations in mind, we wanted to construct a system that is not totally relying on the information in the knowledge base, as it is possible it could be not 100% correct, due to the noise which is omnipresent.

In artificial intelligence, this idea is to balance between these two modes, is called the balancing between exploitation and exploration, respectively. These two modes of algorithm are of a great deal in A.I. and are briefly explained below:

- When the algorithm operates in exploitation mode, it will construct bundles, based on properties or characteristics with the highest reward in the reward
system. Hence, the properties that have the highest probability of generating promising bundles. In this setting, the algorithm totally relies on what is has been learning previously and is eager to exploit this information.

- In exploration mode, the algorithm operates sceptically and is aware of the fact that ‘optimal’ choices, based on the underlying reward system, do not always refer to optimal choices in real-life. Therefore, the system tempts to broaden its knowledge by taking ‘suboptimal’ decisions from time to time, based on the reward system once again, as it realises the noise in the system has a great impact.

Several techniques have been proposed that tempt to find a balance between these two modes as the moment when one or another algorithmic mode is turned on or off is of a great influence to the final result. Remember that in an on-line setting, proposed in section 3.1.1 and 3.1, rewards are calculated and re-calculated as the algorithm runs different iterations. In such a setting, it is obvious that the time when relying and distrusting the reward system is crucial for the outcome and performance of the algorithm.

### 4.1.1 Simulated annealing

One of the techniques that tries to find a balance between exploration and exploitation, is called Simulated Annealing or SA, first presented by Kirkpatrick, Gelatt and Vecchi in 1983 [Kirkpatrick et al., 1983]. SA finds it origin in the annealing or cooling down of solids, a physical process in which a solid is melted and then cooled down slowly in order to obtain perfect crystal structures, which can be modeled as a state of minimum energy, or ground state. To avoid defects or irregularities in the crystal, the cooling needs to be done very slowly [Hoos and Stuetzle, 2004].

We rely on this idea and use a similar criteria to determine on balancing between exploration and exploitation. The ground state represents the state of the algorithm where enough meaningful information is collected to construct a perfect reward system, capable to being used in every setting and benchmark. To achieve this, the algorithm should be prudent in the way it relies on incomplete information, obtained in earlier runs. Hence, the probability of using exploration, \(p1\) (4.1) should be high in initial runs and should be reduced in a steady manner (in consent with the cooling-down phase), then relying more and more on the exploitation phase (4.2), when it is believed that the algorithm has gathered enough reliable information. The temperature \(T\) refers to the temperature used to cool down, influencing the time. Therefore, probabilities are assigned to the two modes and evolve over time. A random number between 0 and 1 distinguishes between
which state is activated. The mathematical models are presented in equations 4.3 and 4.4.

\[ P(\text{exploration}) = p1 \]  \hspace{1cm} (4.1)

\[ P(\text{exploitation}) = p2 \]  \hspace{1cm} (4.2)

\[ P_{\text{new}}(\text{exploration}) = \frac{\text{Iteration number}}{T} \]  \hspace{1cm} (4.3)

\[ P_{\text{new}}(\text{exploitation}) = 1 - P_{\text{new}}(\text{exploration}) \]  \hspace{1cm} (4.4)

### 4.1.2 Epsilon-greedy strategy

Epsilon or \( \epsilon \)-greedy is another technique aiming to achieve the balance between exploration and exploitation. In the TRBS, we are searching for matches between transportation items. Based on the rewards associated with different properties, the system will look for the best combinations of transportation items, meaning that they can be grouped together into a bundle. By looking for the best combination, we mean of course bundles that are very likely to receive interestingly low bids in the auctioning system.

A greedy strategy, is a strategy that selects the best combinations of transport items all the time. More precisely, it always relies on its reward system to make the locally optimal choice at each stage with the hope of finding the global optimum. For many other problems, greedy algorithms fail to produce the optimal solution, and may even produce very bad results, this because it lacks the ability to explore other solution components.

An extension of this technique is the epsilon-greedy variant. Instead of taking the locally optimum decision all the time, in \( \epsilon \) times of the cases, a random move is chosen. In the other \( 1 - \epsilon \) times, the greedy solution is taken. A typical parameter value might be \( \epsilon = 0.1 \), but this can vary widely depending on circumstances and predilections. The benefit of the epsilon-greedy strategy is its simplicity and its capability to escape local minima and find its way up to a global minimum, although this is not guaranteed. In general, much better solutions are achieved in an epsilon-greedy strategy, compared to a full greedy strategy.

It is important to mention that the two ideas above, to balance between exploration and exploitation are only important when used in an on-line setting, where rewards are learned on the way. In an off-line setting, the rewards in the knowledge base remain static and therefore it is of no use to explore.
4.1.3 Simulation

An important aspect of the matching procedure is the problem of creating bundles that are too big. There is need for a criteria that creates bundles up to a certain quantity. Instead of inserting threshold values indicating a maximum quantity, we opted for a small procedure, aiming to simulate the effect of adding an item to an already existing bundle or creating a new one. This is an important aspect of the bundler as it tends to keep adding items to its ‘best matching bundle’. There is need for a discrimination factor to determine when it is opportune to create a new bundle out of the item. The two possibilities, e.g. adding the item to the best existing bundle or creating a new one, are considered by estimating their future reward. If the reward of the bundle, when the item was added is not significantly larger or improving than before, it might not be interesting to assign the item to this bundle, although the matching system chose it. Hence, instead of always trusting on the matching system, which does not output a degree, indicating the quality of the match, this little simulation step is needed to determine when a bundle is full enough. The rule used to discriminate between these two possibilities is given below.

\[
\text{bundle}_{\text{reward}}_{\text{with item}} \times \rho > \text{bundle}_{\text{reward}}_{\text{without item}}
\]  

(4.5)

As value for the \( \rho \) value, we used 1.5.

4.1.4 The algorithm

As the basics of the A.I. techniques are elucidated, the time has come to explain the details behind the Transportation Request Bundling algorithm. Remember that this system receives a set of transportation request items as input and is supposed to produce promising bundles of these items by creating groups that are complementary. Thus aiming to result in a good bids. As already mentioned, the bundling system takes care of the trade-off between exploration and exploitation, where random and so called greedy bundles are constructed, respectively. An outline of the algorithm is presented below:

1. Based on the trade-off function between exploration and exploitation, explained in section 4.1.1, the choice is made to create random bundles or smart bundles, respectively.

2. When the exploration mode is picked, random bundles are constructed. Random in the sense that the reward function is not consulted and transport items combined, (1) regardless of the output of the reward system. To determine the amount of bundles outputted by the system, also a random
number is picked between an interval of \([1..bundles_{max}]\) (2). This to ensure that multiple successive exploration stages do not result in exactly the same bundles, but introduce significant exploration. (1), together with (2) introduces another layer of exploration, next to the techniques mentioned in 4.1 and contribute to the power of the algorithm, as a whole.

3. When the exploitation mode is activated, the reward function is consulted and items are grouped, based on their matching quality, using an epsilon-greedy strategy, as explained in 4.1.2. The simulation step, explained in 4.1.3 is needed to discriminate when a bundle is considered "full" enough and a new bundle should be created.

A brief outline of the main components of the TRBS is given in pseudo code, below.

```
input : S: a set of N transportation requests
output: B: a set of bundles of transportation requests

1 for j ← 1 to MaximumIterations do
   2    Mode ← determineMode(j);
   3     while S ≠ ∅ do
   4         Create bundles;
   5         for i ← 1 to N do
   6             Bundle according to mode;
   7             if Mode == Exploration then
   8                 B = makeRandomBundles(S);
   9             else
   10                Make smart bundles;
   11                X = findBestMatchingBundle(S[i]);
   12                if simulateEffect(X, S[i]) then
   13                    addToBundle(X, S[i]);
   14                else
   15                    startNewBundle(S[i]);
   16                end
   17            end
   18        end
   19    end
20 return B;
```

**Algorithm 2**: Outline of the TRBS algorithm
4.2 Conclusion

In the Transportation Request Bundling System, or TRBS, we have tried to capture different aspects and ideas of the A.I. world when it comes to balancing between exploration and exploitation. We believe there is need for a robust balance between the two modes, as we are well aware that the underlying reward systems consist of incomplete knowledge, based on discretisations and assumptions. For results on this system on several benchmark instances, we refer to chapter 5.

4.3 Chapter’s summary

In this chapter, we have introduced a bundling mechanism that takes advantage of the knowledge bases, earlier presented in chapter 3. The bundling system, TRBS, was presented that aims to find a balance between exploration and exploitation phases, where a certain amount of randomness is introduced and greedy strategies are chosen, respectively. Several ideas and techniques, coming from the A.I. field were introduced, explained and applied to the setting of bundling transportation requests into bundles.

In chapter 5, results are presented of these two bundling techniques on several instances from a benchmark. It is then that we can compare our ideas and will from a base for conclusions and discussions, covered in section 6.
Chapter 5

Results

In the previous chapters, we have explained the details and rationale behind the different reward systems and the bundling mechanism. In these sections, we already provided results on experiments to denote each learning system’s influence on the performance measure. In the following sections, we will briefly repeat some of these experiments and use them to base our conclusions on.

5.1 On-line learning

In a first series of experiments, we focus on the distinction between the on-line and off-line reward system. The performance of the three individual learning systems will be presented.

5.1.1 Previous work

In section 2.1.1, we have covered the limited amount of previous work done in the simulator on the 4PL. Recall that in an earlier stage of the project, researchers proposed to divide the world into equally-sized grids and suggested an outline for an online, unsupervised learning method to learn which regions are more interesting than others. The graph in figure 5.1 denotes the performance of the bundling mechanism, TRBS, using the reward system based on information of the equally-sized grids. The information concerning these location is not optimal or complete at the time the algorithm starts its initial runs, but gradually increases. Figure 5.1 denotes the average price per kilometer for the 3PLs involved in the bidding process. As the goal of the algorithm consists of constructing interesting and cheaper bundles for these companies, the goal is to see the price per kilometer drop over time. This is also the case in their approach, where a final performance of cost of around 65 units is achieved. More information on the configuration used, can
be found in A.1. Despite the fact that the discretisation method and the learning rule are relatively simple, the algorithm is capable of outperforming the simple bundling schemes, such as random and single-item bundling, introduced earlier.

![Graph showing cost per kilometer for 3PL companies](image)

Figure 5.1: The graph in red denotes the cost per kilometer for all 3PL companies involved in the bidding process. The other graphs represent simple bundling schemes which are clearly outperformed.

### 5.1.2 Cluster-based LS

Using a cluster-based reward system and the TRBS bundling mechanism, we can see a final performance in the average price per kilometer of around 61 cost units (figure 5.2). The use of clusters is justified by investigating the distribution of industrial plants. Therefore creating cells based on their density instead of size is more interesting. Using the exploration phases, the bundling algorithm is exploring several bundling schemes to give the underlying reward system the time to construct a general hypothesis. After 7 simulation days, this knowledge is exploited and we see a significant increase in performance.
Figure 5.2: The graph in red presents the performance of the TRBS bundler, running on top of the cluster-based LS. After exploring different settings in initial runs, the algorithm exploits its search towards promising bundles.

5.1.3 Distance-based LS

In figure 5.3, a similar experiment is conducted using only the distance-based learning system. A final, averaged performance of 73 cost units is achieved, which is 16.12% worse than only relying on the cluster-based learning system. Nevertheless, it performs still much better than the simple bundling methods, such as random or single-item bundling. Because of the fact that the distance between pick-up and delivery locations is an important parameter in the calculation of the bid of the 3PL, we believe that one should always add the distance-based LS to the combined system.
Figure 5.3: The graph in red presents the performance of the TRBS bundler, running on top of the distance-based LS. After exploring different settings, the algorithm exploits its search towards promising bundles with a final performance of cost of around 73.

### 5.1.4 Volume-based LS

In figure 5.4, a averaged performance of around 110 cost units was achieved using the volume-based system. We believe we did not manage to fully fine-tune the internal weights and parameters of the volume-based LS to gain knowledge on the preferences of the 3PLs on this matter. Although it is still better than the other, more naïve methods, displayed in the figure, we have used this LS with a small influence in the calculation of the hypothesis in the combined system.
Figure 5.4: The graph in red presents the performance of the TRBS bundler, running on top of the volume-based LS. After exploring different settings, the algorithm exploits its search towards promising bundles with a final performance of cost of around 110.

### 5.1.5 Combined system

By combining the knowledge of the 3 learning systems and weighting them, based on their individual performance, a combined system was created (section 3.2.4). This system relies on the advices of the three learning systems and combines them using weights. An average performance of 48 cost units was achieved. This is a 21.31% increase, compared to the cluster-based system, which was until now the best performing learning system. It also beats the previous proposals from section 2.1.1 by 26.15%. The fact that we did not reject systems that do not perform optimal in previous settings, now pays off. As we believe these systems can still perform promising on future, real-life data, after fine-tuning their components. This, because their presence and rationale is justified.
5.2 Off-line learning

In this experiment, we investigate the performance of the off-line learner. Using a NN, the weights are adjusted automatically in the learning process. The key is to gather good and sufficient data and to let the algorithm run long enough to learn all aspects of valuable bundles. After taking these criteria into account, we have come up with a knowledge base that performs very good and this without manually finetuning any parameters. The off-line system is capable of outputting a cost of around 45 cost units on average. Even outliers up to 43.5 cost units were spotted, this is a total increase of 33% compared to the best learning system so far, the cluster-based LS, in 5.2.
Figure 5.6: Different boxplots represent the minimum, maximum, mean and quartiles of 5 independent runs of the TRBS bundler, running on top of the NN-based reward system. The performance of the 5 runs are similar and an average performance of around 46 is achievable, with outliers up to 43.5.

5.3 Combinational behaviour

One of the things we discussed in the introduced chapter was the fact that 3PL companies do not make their price calculations and internal details public. As explained in section 1.1.4, 3PL companies often charge high prices for transporting goods, because the number of empty kilometers is very high and increasing their costs. A good test would be to conduct an experiment where pick-up and delivery requests are placed around in the world of customers in such a way to easily test whether the algorithm combines items to reach a full truck load or FTL and reduce the amount of empty kilometers. To easily set up such an experiment, we created our own, small benchmark instance and present it in more detail in section A.2.

In this small example, it is easy to test whether the algorithm takes into account that by intelligently combining request from one group to another. As depicted in figure 5.7, the goal is to create bundles of type (a) instead of constructing bundles of type (b), where the number of empty kilometers is very high, together with the LTL.
Figure 5.7: Figure (a) denotes an ideal bundling case where the cost of the 3PL company can significantly be reduced, by combining requests from the two groups in a smart way. In figure (b), a naïve case is depicted where each PDP request is handled off individually, thus increasing the amount of fuel needed and LTL ratio.

Figure 5.8 presents the performance of the TRBS algorithm versus a very naïve bundler, which does not take into account the idea mentioned above. It is clear that by taking into consideration the bundling of return shipments can clearly reduce the costs of the 3PL companies and in this setting 28% reduction was achieved.
Figure 5.8: Intelligent combinations of request items can reduce the 3PLs cost significantly.

### 5.3.1 On-line versus off-line

<table>
<thead>
<tr>
<th>Learning method</th>
<th>On-line</th>
<th>Off-line</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>System</strong></td>
<td>Cluster</td>
<td>Distance</td>
</tr>
<tr>
<td><strong>Average cost per km</strong></td>
<td>61</td>
<td>73</td>
</tr>
<tr>
<td><strong>Diff. with previous work</strong></td>
<td>-6.1%</td>
<td>+12.3%</td>
</tr>
</tbody>
</table>

Table 5.1: The average cost per kilometer is denoted for each learning method, based on the previous experiments. The combined and NN system decrease the cost by 26.1% and 30.7% compared to previous work from section 2.1.1.

Based on the results in table 5.1, we can discuss on the matter of using on-line or off-line learning in the bundling setting of the 4PL. As we can see, using on-line learning, most statistical learning methods achieve acceptable results after a few iterations. The volume-based system is performing the worst, but because we are using an artificial benchmark with little similarities to real-life situations, we choose not to omit this learning system and also rely on its advice in the combined system, but with minimal influence. The combined system is capable of improving the performance of the previous work in the simulator by 26.1%. A
downside of using the statistical rules using weights, is that amount of finetuning involved in these learning systems. Recall that the rules to compute and update the reward for one learning system individually relies on 5 parameters (4 weights and 1 learning rate). For the three learning systems, 15 parameters are involved, plus three weights that denote each system’s influence in the combined system. Thus, resulting in 18 parameters. This makes it hard to come up with a set of good parameters that perform well on all benchmark instances. We believe this is one of the reasons why no results better than 48 cost units were achieved.

The off-line learner, using a NN, on the other hand has got less attributes to its disposal, as the knowledge base is constructed without any location-based information (3.3). Based on 5 individual runs, we have denoted an average performance of 45 cost units, 6.25% better than the combined, on-line system and 30.7% better than previous work on this setting. This is quite remarkable, as using less information, better results were achieved. We believe this is a consequence of using a good training set and by relying on the backpropagation algorithm in the NN, which was capable of constructing a hypothesis that was general enough to perform good on all instances.

### 5.4 K-fold cross validation

As discussed in 2.3, the amount of training data and problem instances is limited. A well known technique from the field of statistics is \textit{K-fold cross-validation} and can be used to overcome this problem. In K-fold cross-validation, the original sample is randomly partitioned into K subsamples. Of the K subsamples, a single subsample is retained as the validation data for testing the model, and the remaining K 1 subsamples are used as training data. This process is then repeated K times (the folds), with each of the K subsamples used exactly once as the validation data. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. As we have access to only 10 input files, we could use 10-fold cross-validation in the experiments. The result of this experiment is depicted in figure 5.9. For each of our 10 instance files, we have used 9 for training purposes and 1 for testing the hypothesis learned. Good results are the one where the instance, not used to train the hypothesis, performs similar to the ones used for training. On the figure, this is depicted by points, which are situated on the blue error bars, indicating the mean and standard deviation. If the point is located on the error bar, the performance of the algorithm on the test instance is similar to the performance received on instances used for training. More precisely, the error bars depict the performance of 68.2% of the training data, assuming a normal distribution. As we can deduce from the picture, on 80% of the
Figure 5.9: On the x-axis, the number of the instance which was not used for training, is displayed and its performance on a testing phase is denoted with a point. The performance of a testing phase on the 9 other instances, which were used to train and learn the hypothesis is depicted by blue boundaries, representing the mean and standard deviation of the average on these testing stages.

cases, the unseen instance is performing similar to instances used for training the algorithm and in two cases, the performance is worse. This result was conducted with instance 1 and 5 and this could be related to the fact that these instances are a harder, compared to the other problem instances. We have noticed that these instances, even though when they were present in the training set, are providing us often with the worse results, e.g. the maximum or worse price per kilometer on average. On the 10-fold Cross Validation experiment, we can conclude that the algorithm, and the logic behind it, is capable to come up with a general hypothesis that can be applied to unseen instances and provides similar results.

5.5 The School Bus Routing Problem

Another, very interesting and practical problem in computer science is the School Bus Routing Problem or (SBRP). Due to the fact there are very few papers pub-
lished on the subject of 4PL’s and the lack of good, experimental data, we been focusing on another problem that could be related to the problem of the 4PL, provided that a problem transformation is feasible. With this, we did the best that we could to overcome the lack of experimental data and the fact that artificial data, we used in the other experiments, do not provide a perfect fit. In the following sections, we will explain the problem into detail and will determine to what extent the problem of the 4PL, where transport items are bundled into groups, can be translated to the SBRP. To accomplish this, we present another benchmark instance of school bus data, from a school located in Riverdale, New Jersey.

5.5.1 Problem description

The SBRP is closely related to the standard Vehicle Routing Problem or VRP, which is a popular research area for the last three decades. VRP is a problem which finds the optimum routes that a vehicle travels in order to serve customers residing in a geographically dispersed area. The SBRP has same characteristics with VRP in several ways; however, there are noticeable differences. While a typical VRP mostly deals with freight transportation, the SBRP is related to student transportation. The additional requirements of the SBRP focus on human satisfaction and effectiveness while traveling. Because of those reasons, SBRP is more complicated problem than the VRP [DEMIRAL et al., 2009].

The School Bus Routing Problem (SBRP) can be specified as follows: a group of spatially distributed students must be provided with public transportation from their residencies to the school. Three factors make school bus routing unique: efficiency (the total cost to run a school bus), effectiveness (how well the demand for service is satisfied) and equity (fairness of the school bus for each student). In this experiment we will focus on routing the buses to the bus stops.

5.5.2 Previous work

As previous work, we rely on a paper, published in 2001 by Spasovic et al. ([Spasovic et al., 2001]), where several attempts have been made to optimise bus routes between from neighbourhoods in New Jersey to a school. We will present their work now.

The case study discussed in the paper involves the Riverdale, New Jersey, elementary school where there are 199 students bussed to the school in the morning. The school clustered the students into groups associated with 24 bus stops. The buses are required to depart and return to the school within an allotted half-hour time period, subject to the bus size constraints. This ensures that all students remained on the bus for an equitable time period.
The school bus routing problems can be presented conceptually as a cost minimization problem, in which the objective function is the total operating cost. The objective function can be minimised, subject to a series of constraints, listed below:

1. The time that students spend for traveling on the bus must not exceed a given (or externally specified) limit, which is set to 30 minutes.
2. The number of students per bus must not exceed the number of seats available on the bus.
3. Each bus stop is allocated to exactly one bus.
4. Every route must have at least one bus stop.
5. Each stop is allocated to only one bus route.
6. The number of buses leaving the school must equal the number of buses returning to the school.

Some of the constraints might seem trivial, but are necessary to correctly formulate the problem. The following parameters are used in the mathematical formulation.

1. $T_{max}$, maximum time available for the bus to pick up students on a route
2. $s_{ij}$, distance between node i and j (in miles)
3. $t_d$, dwell time of the bus at a node (in hrs) per student. The time specified for one student to enter the bus, show his identification and to take seat
4. $d_i$, demand (number of students) to be picked up at node i
5. $\delta_{k,t} = 1$ if bus route k has bus type t, 0 otherwise
6. $O_t$, operating cost for type t bus (in $/bus-hr)$
7. $Cap_t$, seat capacity for type t bus (in seats/bus)
8. $V_t$, average speed for bus of type t (in miles per hour)
9. $X_{ij,k} = 1$ if nodes i and j are catered consequently by bus k.
The objective is to minimize total operating cost \( Z \) that is formulated as

\[
Minimize \ Z = \sum_{k=1}^{l} t_k \left( \sum \delta_{k,t} O_t \right)
\]  

(5.1)

Where \( l \) represents the total number of bus routes, \( t \) represents the different types of buses and \( t_k \) is the time taken for bus \( k \) to pick up students on \( k_{th} \) bus route and drop students at node 0 (e.g. the school,) is computed as

\[
t_k = \sum_i \sum_j \left( X_{ij,k} s_{ij} / \sum_t \delta_{k,t} V_t \right) + 2 \times \sum_i \left( \sum_j X_{ij,k} \right) d_i t_d
\]  

(5.2)

In the case of the Riverdale elementary school, three types of buses are used, with a capacity of 54, 20 and 16, respectively. Their operational cost is $60, $50 and $45 per hour. In the paper by Spasovic, an illustrative map is attached of the school’s neighbourhood, together with its 24 bus stops.

Figure 5.10: An illustrative representation of the 24 bus stops, together with the amount of students, denoted by stars. The school is depicted by a larger dot. Source: [Spasovic et al., 2001]

Their results consist of three solution approaches, a time-savings heuristic, a mixed-integer linear program (MILP) called Router and a sweep method. These approaches consist of route optimisation techniques and analytical methods. For each of the methods, the results achieved are presented in A.3. For more insights on the detail of these three methods, we refer to the original paper [Spasovic et al., 2001].
5.5.3 Problem transformation

In the bundling problem of the 4PL, shippers provide the 4PL with transportation requests that have to be assigned to carriers. In the SBRP, the transportation requests are represented by bus stops, each with a fixed amount of students to be picked up. These students will be picked up at their assigned bus stop and be transported towards the school. The carriers are represented by bus companies, each with a fleet of buses of a certain type with different characteristics, such as capacity and costs per hour. The 4PL, on its turn, learns over time which groups of bus stops are interesting to be grouped together, on location, distance and volume properties, as explained in section 3. The auction house will determine the winner of each bundle or route and notify the 4PL. This scenario is depicted in figure 5.11.

We recreated the setting by Spasovic et al. which consists of three bus types with a capacity of 54, 20 and 16 seats and a cost of $60, $50 and $45 per hour, respectively. As in Spasovic’s work, the 4PL receives the total lot of 24 bus stops.

![Figure 5.11: An illustrative representation of integration of the 4PL bundling solution to the School Bus Routing Problem. Each 3PL represents a different type of bus, with different characteristics and cost. The bid they place in the auction house represents the cost of assigning their bus type on the route in the bundle. The auction house will assign the bundle to the cheapest bidder.](image)

Challenges

Although this approach seems a good idea, there are some problems involved in the translation. More specifically, Spasovic et al. did not provide us with all necessary data to easily make the translation. A first major element that was missing to redo their experiment, was the geographical input data. No links to external resources were provided in the paper, besides the map of the neighbourhood of
Riverdale’s elementary school in 5.10. Therefore, we closely examined the illustrative map and a geographical map of the area, hosted by Google Maps. By zooming in on the different bus stops in the figure, we were able to retrieve the real longitude and latitude coordinates of the bus stops, but with a small estimation factor as one can not be completely sure that the coordinates we retrieved match the coordinates used in the paper. To calculate the distances between the bus stops, one can not rely on the simple Euclidean distance metric for this task, as the distances used in miles are used in the calculation of the original objective function and therefore, we need to transform longitude and latitude coordinates to distances, expressed in miles. To accomplish this, we used the Great Circle Distance formula\(^1\) to calculate the distance between 2 points, denoted by \((\text{lat}_1, \text{lon}_1)\) and \((\text{lat}_2, \text{lon}_2)\), respectively:

\[
 r \times \text{acos}\left(\sin(\text{lat}_1) \times \sin(\text{lat}_2) + \cos(\text{lat}_1) \times \cos(\text{lat}_2) \times \cos(\text{lon}_2 - \text{lon}_1)\right) \quad (5.3)
\]

Where \(r\) is the radius of the Earth and can be used to specify in what measurement should be used to represent the result.

- \(r = 3437.74677\) (nautical miles)
- \(r = 6378.7\) (kilometers)
- \(r = 3963.0\) (statute miles)

In our setting, we used the latter as it in the United States statue miles are used to denote distances. One should notice that this formula requires that the Earth is a perfect spherical shape. In practice, this is not the case, as the Earth has a near-spherical shape. This is another estimation we have to take into account. A final parameter that was not defined in their experiments was the dwell time, \(t_d\) in hours/student. After setting all the previous parameters, the dwell time was set to 0.00225 hours per student (or 8.1 second/student) after calibrating the objective function on the previous results in A.3. The results of the calibration is listed in 5.5.3.

\(^1\)http://www.meridianworlddata.com/Distance-Calculation.asp
Table 5.2: The objective function we used is subject to several estimations and approximations. Nevertheless, the objective function values we receive on the previous results are very close. On the first result, the objective function value is still 6.2% away from the correct value but the two following results are almost identical.

Although our input data and estimations are not identical to the objective function used in the previous paper, we seem to have managed to come up with a good approximation of all missing parameters.

5.5.4 Results

In our newly created setting, the 4PL component will apply its reinforcement learning algorithm to learn over time promising and interesting location, distance and volume characteristics of bundles of bus stops. This, only based on the bids of the bus companies, calculated by equation 5.1. We ran the algorithm in the simulation environment, where exploration and exploitation techniques are used to create bundles, based on the knowledge, gathered on previous runs of the algorithm. The best result obtained consist of 6 routes for the different buses, with a total cost of $109.86 as presented in table 5.5.5, which is very comparable to the solution obtained with Spasovic’s experiments. The 3PLs, representing the bus types placed a bid on these bundles and the lowest bid was assigned to it. Notice that the last two routes, 6 and 6.1 were actually created out of one bundle. From the calculations of the 3PLs, it was cheaper to arrange two buses with 20 seats than one bus with 54 seats. This setting would have costed $27.40. As these two routes are quite short, it might be possible that the same bus can serve both route 6 and 6.1 within $T_{max}$. Also, it is quite remarkable that bundle 4 was auctioned off to a bus with 54 seats, as it comprises 19 students, which would result in almost 100% capacity utilization when a bus with 20 seats was used. The reason behind this is that the PDP solver of each of the 3PLs, representing the buses, is focused on minimising the total distance instead of maximising the capacity utilisation, as this is only a secondary objective of the PDP solver. By investigating the results, the cost of the bus with 20 seats for bundle 4 was $18.05, which is almost 2 dollars more expensive than what the bus with 54 seats offered. The PDP solver of the bus with a capacity of 20 divided the bundle into two, distinct
routes, namely $0 - 11 - 10 - 0$ and $0 - 13 - 12 - 0$. The final cost of all the routes combined is $109.86$, which is only a few cents worse than the ROUTER methodology, mentioned in section 5.5.2, this, if the objective function and our estimations are accepted, but when comparing the calibration in table 5.5.3, we believe this is the case.

5.5.5 Conclusion

In the previous sections, we have presented and discussed the School Bus Routing Problem. We have elaborated on previous work done at the New Jersey Institute of Technology in Newark [Spasovic et al., 2001], by Spasovic et al. We have tried to transform the SBRP to an instance the 4PL was capable of working with, which comprises assumptions and estimations, together with geographical input data we gathered ourselves. As we have seen, after some slight adaptations to the simulator, the 4PL was capable of creating bundles out of the bus stations, with a best price of $109.86$, which is comparable to earlier results achieved. This result comprised 6 bundles and 7 PDP routes, 2 routes extra compared to previous solutions (A.1, A.2 and A.3).

In the solution approach by Spasovic, the school is the central component which runs the different PDP solvers on the benchmark with 24 bus stops. Each algorithm’s goal consists of finding the best allocations of bus stops to three types of buses. Each of these mechanisms relies on specific information on the bus companies and tries to further optimize the routes, based on a certain objective function. Their traditional approach requires the school to acquire the information on the buses and the complete objective function to be known beforehand.

Using our approach, the school does not act as a central component, but is considered the shipper, providing a coordinator with 24 transportation requests, representing bus stops. This coordinator, the 4PL, together with the auction house is responsible for contacting interested transportation firms. The auction house allows flexibility in contacting and negotiating with several transportation suppliers at the same time, as it uses an open market. Therefore, the approach, proposed in this paper, is more distributed and does not require a central component to acquire information on all aspects a transport company could take into consideration while computing its costs. These aspects make our approach more general and more applicable to a real-world setting where the school can outsource its transportation needs in a competitive setting.
<table>
<thead>
<tr>
<th>Bus</th>
<th>Route</th>
<th>Number of Stops</th>
<th>Number of Students</th>
<th>Vehicle Capacity</th>
<th>Capacity Utilization</th>
<th>Operating Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0-16-17-15-14-0</td>
<td>4</td>
<td>35</td>
<td>54</td>
<td>64.81%</td>
<td>$17.68</td>
</tr>
<tr>
<td>2</td>
<td>0-22-20-19-18-0</td>
<td>4</td>
<td>28</td>
<td>54</td>
<td>51.85%</td>
<td>$20.37</td>
</tr>
<tr>
<td>3</td>
<td>0-5-6-7-8-9-0</td>
<td>5</td>
<td>44</td>
<td>54</td>
<td>81.48%</td>
<td>$17.28</td>
</tr>
<tr>
<td>4</td>
<td>0-12-13-11-10-0</td>
<td>4</td>
<td>19</td>
<td>54</td>
<td>35.18%</td>
<td>$16.18</td>
</tr>
<tr>
<td>5</td>
<td>0-24-23-0</td>
<td>2</td>
<td>17</td>
<td>20</td>
<td>85.00%</td>
<td>$12.85</td>
</tr>
<tr>
<td>6</td>
<td>0-4-3-0</td>
<td>2</td>
<td>19</td>
<td>20</td>
<td>95.00%</td>
<td>$25.50</td>
</tr>
<tr>
<td>6.1</td>
<td>0-2-1-21-0</td>
<td>2</td>
<td>17</td>
<td>20</td>
<td>85.00%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>24</td>
<td>199</td>
<td>278</td>
<td>71.16%</td>
<td>$109.86</td>
</tr>
</tbody>
</table>

Table 5.3: The best result achieved with the bundler consisted of 6 bundles, that resulted in 7 PDP routes. The total cost of the school bus routes is $109.86.
5.6 Chapter’s summary

In this chapter, we have presented the results on the different learning systems and additional bundling technique. Several results were promising, even although our testbed of problem instances is quite limited. We have seen that some of the statistical learning systems perform very good individually, where others lack the capability to learn a very good hypothesis every time. In a combined setting, where each learning system is assigned a weight, reflecting its importance in the total calculation, we have seen that the results are better and in fact very good, with a 26% increase compared to previous work done in the simulator on this setting.

The neural network is another way to construct a knowledge base, but this time less features or characteristics of bundles are used as input. Nevertheless, the bundler is performing even better with this knowledge base installed. The advantage of this approach is that it consists of an off-line learner were the hypothesis is static and will not be adjusted on the way. This allows the bundler to exploit its information all the time, giving very good results on average.

We have also examined the setting the school bus problem, an optimisation problem, closely related to the bundling problem of the 4PL, but this with some modifications and adjustments. We have translated one problem into the other and were able to retrieve data used in a previous experiment, this with some assumptions and estimations. We did not rely on commercial PDP solvers as in [Spasovic et al., 2001], but nevertheless, we were able to come up with similar results. We believe our approach to solving the SBRP is more general and flexible to be adopted in a real-world setting, where a shipper, in this case the school, wants to outsource transportation activity in a very competitive setting between several interested transport companies. to the best results obtained in the paper, concerning the previous work.
Chapter 6

Discussion & conclusions

In this chapter, we will present an extensive overview of the thesis, with all its components. This summary will comprise all chapters we introduced earlier and will reflect on the contributions of our work. Furthermore, we will discuss the advantages and limitations of our proposals, together with ideas on future work.

6.1 Summary

The thesis is conducted in the domain of supply-chain management and transportation logistics. In this branch of economics, the structure of the organisation is decoupled into independent divisions to reduce the complexity in the decision making of several managerial decisions (section 1.1.1). This division is also carried through to the level of organising the flow of materials and partial products that lead to the final, finished product. These components of the final product the manufacturer offers to the market are assembled at different plants at possibly different locations and have to cross both manufactural as geographical borders to meet the market globalisation. To allow goods to be picked up and delivered from one location to another, manufacturers have to rely on other companies, specialised in logistics. These logistics companies are called Third Party Logistics or 3PLs and provide a fleet of transportation equipment to make sure the goods are transported at the correct site of the manufacturer or assembler, involved in the supply-chain. Transportation is a very prosperous industrial branch, with a yearly turnover of $124.1 billion dollars in the United States in 2010 and was one of the first economies to recover from the economical crisis in 2009 (1.1.3).

Because the introduction of supply-chain management involved the separation of a company’s internal affairs, based on their functionality, coordination of the overall system is an issue, as stated by Thomas and Griffin [Thomas and Griffin, 1996]. A rather new component was introduced to fill this gap and orchestrate the supply-
chain for all companies in such a way that transparency and a fair price setting was ensured. As cited by Robu [Robu et al., 2008], in the Netherlands in 2008, the average transport performance was only optimal in about 40%-60% of the cases and there is room for significant improvement in the utilization of the transportation equipment, such as trucks. This component is the Fourth Party Logistics or 4PL, a consulting firm specialised in the planning of the supply-chain and is in close contact with the 3PL companies in its area. The 4PL company acts as a buffer between the manufacturers and carriers (3PLs), where it aims to find convenient delivery options for the transport requests of the shippers and finally distribute them across carriers that applied for these orders. This can actually be cheaper than the setting where a customer contacts one or more carriers individually to arrange a contract, as smaller transport companies often do not have the complex cost structure that larger companies have [van der Putten et al., 2006]. For smaller carriers it will then be easier to find orders that fit their transport equipment, without overdoing themselves by accepting (too) large orders that they can not manage in the end. In short, as transportation needs became even more complex, another type of logistics company started to appear that solely focuses on orchestration and coordination.

As the 4PL is a relatively new company, proposals on how this transparency and flexibility can be ensured are rather limited. Also, research in research as literature, benchmark instances and supporting companies that can provide real-life data are minimal or non-existing. One of the projects that believes in the opportunities the 4PL can offer and aims to fill this gap in the research community is the Distributed Collaboration using Multi-Agent System Architectures project or DiCoMas\(^1\), in short. This project, funded by the IWT\(^2\) and conducted at the CoMo lab at the Vrije Universiteit Brussel, is aiming to provide a reusable software architecture that supports the development of applications for automated collaboration between business processes and thus, one of its applications consists of exploring the possibilities of adding a 4PL to the supply-chain management scene.

In the literature, proposals on how a 4PL could introduce transparency and flexibility in price settings to transporting goods are rare. As the 4PL acts as a buffer between manufacturers and 3PL companies, it should find interesting, correct and fair delivery options for both parties. To the best of our knowledge, only one idea to accomplish this goal is elaborated and published by Robu et al.[Robu et al., 2008]. In that paper, they propose one-to-one negotiation techniques between agent-mediated electronic markets that transcend the sale of uniform goods. They believe that, through negotiation, suppliers and consumers can reach complex agreements in an iterative way, which better matches the needs

\(^1\)http://distrinet.cs.kuleuven.be/projects/dicomas/
\(^2\)http://www.iwt.be
and capabilities of different parties. In more detail, they create an explicit model of the buyers utility function, in the form of a utility graph. Robu et al. were supported by Vos Logistics, a 3PL located in Holland, to provide real-life data of 6000 transportation orders. Their results have stated to reduce the company’s cost by 19% if their model is adopted and used in practice. In order to protect the competitive advantage of Vos Logistics as well as the privacy of their customers and associates, much of this analysis was not reported and therefore could not be used in our thesis as a comparison. We were unable to acquire any real-life data from real 3PL companies, but had to rely on the artificial Li and Lim benchmark [Li and Lim, 2001], which was transformed for this purpose.

One of the contributions in this thesis consists of exploring the possibilities of the 4PL component in the supply-chain. The idea behind our proposal is to elaborate a technique called bundling and auctioning. The motivation behind this idea was first mentioned by Robu [Robu et al., 2008] and was proposed as promising future work for his one-to-one negotiation technique. He proposes to introduce an auction house as an open market technique to increase the competitive edge between the contestants.

To be more precise, in this bundling behaviour, the objective of our 4PL is to capture the 3PL’s preferences on transportation requests. It could be that for some 3PLs their costs and also the price they charge for transporting a set of goods will increase exponentially when the bundle’s properties exceed certain thresholds. A very practical example could be the capacity utilisation of a truck that exceeds 100% or a full truck load (FTL), which means the loads it needs to carry is larger than its capacity. To transport the items in the bundle, the 3PL company should arrange multiple trucks for the same group or bundle of transportation requests, significantly increasing their costs and expenses, which represent fuel consumption, driving hours, maintenance and much more. Not only preferences or properties of a carrier play a role in the calculation of the price, but also the contents of the bundle. Section 1.1.4 explains the setting where complementary transportation requests, specifying the pick-up and delivery locations, can reduce the 3PL’s costs by reducing the amount of empty kilometers, when a truck is transporting no load, but driving to its next pick-up location. Our thesis is conducted with these problems in mind and wants to investigate that when using artificial intelligence and machine learning techniques, the 4PL can deduct the preferences of the 3PLs and exploit this information while bundling. This, to achieve good and fair prices for all stakeholders in the supply-chain.

For the 4PL to address and contact a set of 3PLs, which will transport the goods from the customers, the notion of auction house (section 1.7.1) was introduced. In an auction house, agents represent carriers that can connect to a virtual auction house, where they can place bids on items, being auctioned. The items themselves are bundles of transportation requests. These transportation requests
describe transportation activities demanded by the manufacturers, which want to have their products transported. These requests consist of all the necessary data (e.g. geographical coordinates, volumes and timing constraints) to conduct the physical transportation. The bids are the requested prices of the 3PLs they wish to receive in order to perform the physical transportation activity of the requests or items in the bundle. In order to determine this price (or bid), the 3PL estimates its costs of executing the delivery by examining the contents of the bundle, which is being auctioned. On the one hand, when a carrier asks a high price for transporting items, it can increase its profit, but due to the competitive setting in the auction house, it will not win any auctions and its business will suffer as it cannot provide its employees with enough work. On the other hand, when a 3PL is asking a lower price than its actual costs, he will obviously win a lot of auctions, but its company will not be able to earn any profit. Therefore, using the competitive edge of the auction house, the carriers are encouraged to place honest bids that reflect their actual costs. An auction house introduces one-to-many negotiations, increasing the competition between 3PLs to place honest bids, reflecting their true costs. Thus, a contestant has little to no incentive to lie about its costs as it is negotiating with multiple parties at the same time. Only the agent with the lowest bid receives the bundle which is being auctioned.

Each 3PL company has its own fleet of trucks and a history of transportation orders, where details on the truck’s capacities and current or home locations are stored, together with information on fuel consumption, driving hours and much more. If this information was public, a model to bundle transportation requests in accordance to these preferences could be quite easily constructed by the 4PL. But due to the company’s internal policies and privacy issues, this information is not public and only bidding information is. Thus, the only feedback provided to the 4PL to actually learn the preferences of the bundles is by the bids in the auction house. This is where artificial intelligence comes into place. In the literature [Vovk et al., 2005], artificial intelligence and machine learning techniques have been examined in a learning environment, where an agent needs to learn how to perform a certain task correctly by maximising a certain reward function. However, it has never been applied to the setting of a 4PL aiming to learn bundle preferences of 3PL companies and this is exactly what we did in this thesis. By bundling in accordance to the preferences of the carriers, the 4PL can offer interesting and cost-efficient solutions to the transportation firms and they will be encouraged to use the auction house, although competition is highly present.

Our approach consisted of two parts; (a) learning and deducting the preferences of the 3PLs involved in the auction house and (b) bundling in accordance to the information in this knowledge base. In a first phase (3) of the thesis, we examined the properties of the bundles that could have a high impact in the calculation of its price by the 3PL. The properties we came up with, were location,
distance and volume. The location or the areas the pick-up and delivery requests of a bundle cover have an high influence as some regions are more fruitful and other, meaning that the area comprises many other pick-up and delivery requests, that can be combined to reduce the amount of empty kilometers, explained earlier. As the initial world of customers is not divided into regions, we came up with our own division and used the k-Means (3.2.1) clustering algorithm to divide the world of customers into regions or cells based on its density. Next to the location, the distance between the pick-up and delivery locations is also important as this influences the amount of fuel and driving hours needed to complete the task, directly influencing the cost of the carrier. The volume on the other hand introduces implications on the number of trucks or other transportation equipment needed to cover the bundle. Reducing the number of trucks to a minimum will decrease the costs significantly.

To create a learning system, based on artificial intelligence, there exist multiple possibilities. The major differences between learning techniques lies in the difference between on-line and off-line learning, explained in section 3. In our thesis, we propose techniques for deducting the preferences, mentioned earlier, for both cases. In the on-line system, in section 3.2, rewards are calculated and updated using statistical techniques, capable of capturing normalisation, mean and variance in the bidding data while constructing an hypothesis. In this on-line learning system the hypothesis is constructed and updated on the way after investigating each instance individually. For each of the properties: location, distance and volume, a hypothesis is constructed and can be used to bundle items together. Throughout the chapter, we have verified and justified this using experimental settings, where multiple carriers bid on bundles, which are constructed with special care for each of the individual preferences. Due to the lack of instance data, it is hard to examine the real performance of each learning system and we limited to comparing the bundling method against naïve or simple bundling schemes such as random bundling and single-item bundling. Nevertheless, each of the learning system taking into account the bundle’s locations, distances and volumes clearly outperform these other metrics. The best results were achieved with the location-based learning system and in the DiCoMas simulator, the 3PLs seem to be under a high influence of the locations of the pick-up and delivery requests and thus also the fruitfulness of each region. The distance (3.2.2) and volume (3.2.3) learning system do not provide the best results, but their existence is justified by the fact that in our experimental settings only artificial data is used from a collections of problem instance files that do not map completely to the 4PL setting. We believe that if this idea would get adopted to a real-world setting, the distance and volume characteristics of a bundle are crucial properties and one should not ignore them. We also provided a combined system in the thesis, which is able to combine the advices of each of the individual learning systems, thus location, distance and
volume learning system. Weights are used to denote the importance of each sys-
tem and to combine them into a single hypothesis. These weights are determined using an experimental approach where they were finetuned to obtain the best re-
results. This combined setting provided us results with bundles which were 26% more cost-efficient, compared to previous work done in the DiCoMas simulator (section 5.1). The downside of this approach consist of the fact that in the on-line system we created our own learning and update rule, based on several statistical measures. Each of the on-line learning systems contains 6 parameters, which can tweak the behaviour of the system using weights. As in the combined system, we rely on the knowledge of three learning systems, the number of parameters that can be finetuned manually, increases up to 18. A solution to this problem was found by investigating another learning technique that does not suffer from finetuning a large set of parameters.

Another way to deduct the preferences and to which degree these preferences influence the final costs, consists of using an off-line method. Off-line learners consist of a training phase where the hypothesis is trained using a set of input instances and remains static after this phase. This implies that the learner should not adjust its hypothesis anymore and can test its model very fast when new in-
stances arise. We used a neural network to map input, represented by the bundle’s properties to an output, represented by a reward indicating the interest of the input bundle to the 3PLs involved in the auction house. We have proven (section 3.3) that the NN was capable to construct a hypothesis, specific enough to deduct the importance of certain properties on the training data, but also general enough to be applied to new settings where unseen instance data is provided. The results on the NN were even 4.1% better than using the combined system in an on-line manner. The conclusion on on-line versus off-line learning in this setting is as follows; in the on-line approach, we continued working on a system based on statistics that introduced a serious amount of parameters that can be finetuned by the user of the system. But due to the amount of parameters and the impact it has on the behaviour of the system, it is relatively inconvenient to find an optimal set for all the 18 parameters that make the learning systems perform very well on every instance file. In the off-line system, we do not suffer from these problems as the backpropagation algorithm in the neural network itself updates the internal weights and the user of the system does not need to intervene. We believe this is the major reason why the off-line learning system is capable to come up with results that are 4.1% better than the ones obtained from the on-line system. Also, because the neural network is used in an off-line setting and the training phase is only conducted once, the algorithm is capable to exploit its knowledge from the start and obtain good results. This compared to the on-line algorithm that needs to adapt its hypothesis on the way and is only capable of providing good results after a series of initial runs with poor results. The key challenge for the off-line
system lies in the fact of obtaining a representative and large training set. In our setting, we trained the neural network with 5831 example instances, representing previously bundled items and a label, indicating the interest of the 3PLs for each bundle, in correspondence to the bid obtained.

The second (b) phase of the thesis consisted of using the knowledge base, whether constructed on an on-line or off-line manner, as a guidance to create bundles that satisfy these preference criteria. Throughout multiple iterations, we assign transportation requests to bundles in accordance to the knowledge base, constructed earlier. The bundling method we propose heavily relies on exploration techniques such as $\epsilon$-greedy action selection and simulated annealing. It also comprises functionality to simulate the effect of adding a request to a bundle or creating a new bundle out of the individual request. These actions are considered, aiming to construct optimal or close to optimal bundles in the end. It is important to notice that when using an off-line learner to construct the knowledge base in the background, the exploration phases can be omitted.

Experimental settings on the learning aspect (5.1), bundling aspect (5.3) have proven that using A.I. and machine learning techniques, it is possible to deduct the preferences and use the information to bundle in accordance to these preferences to reduce costs. It clearly outperformed naïve or simple bundling in these experiments. The fact that real-life data is not available and we had to deduct the tests with only 10 instances of an artificial benchmark is a pity as it influences the industrial value of this thesis. We have successfully applied different statistical techniques that can be used to overcome this problem with the lack of input data, such as the k-folds experiment (5.9), which was successful. In section 5.5.3, we have translated our solution approach to the bundling problem to the domain of the School Bus Routing problem (5.5) or SBRP to denote the practical value of our techniques and their application to other domains. We have countered a solution approach by Spasovic et al. [Spasovic et al., 2001] who used optimisation and heuristic methods to solve the SBRP. Using approximation and estimation techniques we were able to translate the problem and receive similar outcomes, with minor adjustments to the simulator. We have seen that the flexible and distributed approach the combination of bundling and auctioning offers, can also be applied to other practical settings, such as the SBRP. Using this elaborated experiment, we have experimentally proven the applicability of the bundling problem to another problem, with similar objectives, e.g. separating items across a series of clients.
6.2 Contributions

In this thesis, we have provided a theoretical overview of the economical background of supply-chain management. We have informed the reader with details on each of its parties and gave a survey of the latest and state of the art ideas in this field. Also, the connection between this economical domain and computer science have been examined. The main principles of computer science, or artificial intelligence to be more precise have been elaborately presented and are used as a starting point to exhibit our contributions.

Another contribution of this thesis is that a generic solution approach to the bundling problem has been proposed. We have adjusted the design of the DiCo-Mas simulator in such a way that a modular design is achieved and alternative reward systems or bundling techniques can easily be added. The reward system on one hand is now enriched with an on-line and off-line learner, capable of learning the bundle preferences of agents representing 3PL companies, using minimal feedback. Using the bids, information on location, volume and distance have been deducted, using estimation and approximation techniques. Experiments are conducted to evaluate the performance of each of the algorithms proposed and act as a base to form conclusions.

In earlier proposals, the competition between the 3PLs was omitted by performing one-to-one negotiations, allowing 3PLs to place prices on transportation requests that do not reflect their costs completely. Thus, a lack of controllability and transparency for the manufacturers of these goods as they have not that many options to choose from, because at the end of the day the goods have to be on their right locations. Our solution approach, where we elaborated the idea of combining bundling behaviour with an auction house, can be the solution to increase the trust between the different parties. In the auction house the competition between the firms is not omitted as before but instead is shifted towards the auction house in the form of one-to-many negotiations between 4PL and carriers. As bundling in accordance to the 3PL’s preferences without disobeying any privacy issues, result in interesting bundles, the 3PLs are encouraged to rely on the auction house to communicate indirectly with the manufacturers. The combination of bundling and auctioning can be considered a compromise between the manufacturers and carriers, as both parties gain from using this methodology. The fact that these preferences can be learned, even though the available information is limited, is experimentally suggested in this thesis and opens the doors for more studies involved in conducting more practical experiments to allow this idea being adopted by the real stakeholders of the supply-chain. Recall that the main goals the 4PL are transparency and and fairness throughout an orchestrating component and we believe that this is one of the main advantages achieved by this thesis. The approach we propose in the thesis is general enough to be applied to problems
from other research domains, like the School Bus Routing Problem, as we have presented and is therefore not limited to only being used by the 4PL.

6.3 Discussion

The limitations involved in this thesis are more of a data issue than of a model issue. Acquiring the right and correct amount of input data, correctly reflecting the situation in real-life is a key-point in making a success out of our proposals. As we already have mentioned before, the data we used was of an artificial kind and not created with the bundling problem of the 4PL in mind. It was data from a pick-up and delivery benchmark, often used in route optimalisation, but was our only option to actually perform experiments. This implies, in our eyes, the main limitation of this thesis.

For the idea of bundling to be adopted by the real-world stakeholders of the supply-chain, a climate of trust should be created between the 4PL and the 3PLs. The 3PL companies should be made clear that a situation of 40%-60% of transportaton performance [Robu et al., 2008] in the logistics sector is not robust and promising for the future. These companies should therefore be convinced to adopt this idea and to look to the future. At the moment, these carriers are too focused on the short term of organising transportation activities and the idea of adding a 4PL with an auction house allows the companies to focus their attention on future prospects and opportunities on the long term.

The bundling approach, we propose, allows the 3PLs to obtain bundles that reflect their interest and manufacturers to receive fair fees and invoices. In the thesis, we have seen that learning how to bundle can be achieved using artificial intelligence, without the carriers having to reflect on these preferences or to publish any privacy-related content on the company’s profile. Our approach assumes however that manufacturers only rely on one 4PL instance to distribute their transportation activities. If manufacturers contact several 4PLs, it is possible that transportation requests are assigned to multiple carriers. This is not a limitation of our solution approach, but is a concern of the manufacturers, themselves.

This statement also holds for carriers that connect to multiple auction houses at the same time. It is possible that certain 3PLs do this to have access to larger sets of transportation requests. They then work on a hidden agenda and will place bids in auction houses that do not fully reflect their expenses. Only if the reward system on the 4PL’s side, processing the false bids, is working in on-line modus, it will adjust its model and bundles will be constructed that reflect on this model. These bundles will thus not fully cover the 3PLs desires, but nevertheless, the 3PLs have to bid on transportation activities, as else their business will be put off and they will perform poorly. Therefore, it is both for the manufacturers as for
the carriers important to only rely on the services of one 4PL, as only then the bundling behaviour behind it can fully learn their preferences and bundle accordingly to increase the cost-efficiency.

These limitations, concerning the assumptions in our approach are minimal and do not change any of our statements, made earlier.

6.4 Future work

In the future work of the thesis, we will propose aspects of our work that could be more refined. A list of proposals is given below:

- As already mentioned in 6.3, a thorough experimental study should be conducted, aimed to investigate the possibilities of bundling in the supply-chain and impact on all stakeholders involved. This can be a study, focused on the aspect of computer science to the bundling problem, but can also be conducted in a more economical setting, where the requirements of all involved are collected and translated into a model that everyone agrees. Only this can guarantee a full adoption of this proposal in real-life.

- In section 5.5.3, the bundling problem of the 4PL has been translated into a problem instance of the School Bus Routing Problem in Riverdale, New Jersey. It would be nice to see if the bundling problem, e.g. distributing goods towards clients with each different needs can be translated into other problems aiming to optimise a distribution. A possible set of problems could be optimisation problems, such as the Set Covering Problem [Caprara et al., 1998], with all its real-life applications such as solving airline crew scheduling problems.

- The combination of statistical learning systems in the on-line system requires the calibration of 18 parameters. This is a not trivial task to do by hand, as each parameter implies different behaviour of components in the DiCoMas simulator and influences the final outcome. Systems that allow automatic algorithmic tuning, such as F-Race [Balaprakash et al., 2007] allow the evaluation and selection of parameters by using statistical tests that evaluate the statistical significance of each setting. An experiment with a similar tuning system could allow improvements in the results currently obtained with the on-line system and is therefore worth investigating.

- The bundling software at the moment only takes into account location, distance and volume information of transportation activity. Time-windows or other constraints are currently not elaborated in the DiCoMas simulator and could be added to construct a more realistic setting.
6.5 Conclusions

In this thesis, we have learned that adding bundling behaviour to the 4PL, together with an auction house can be a solution to increase the trust and fairness between the firms involved in the supply-chain. In the DiCoMas simulator we constructed a model that is able to deduct preferences of the 3PLs when it comes to bundles of transportation requests.

We believe that a solution approach to fix the lack of trust and performance in the supply-chain can be overcome by introducing one-to-many, instead of one-to-one negotiations between stakeholders, as then the competition between the bidders can be exploited. In this thesis, an specific proposal on how these one-to-many negotiations can be applied between 4PL and 3PLs has been elaborated. We have validated our work on the bundling methods and other ideas using experimental settings and metrics. Before a combination of 4PL and auction house can be applied in real-life, the stakeholders of the supply-chain should become aware the lack of performance that is currently present in the supply-chain. They should investigate literature and proposals that provide a way out of this impasse by increasing coordination in the supply-chain, with fair prices and optimal allocations as a result. We believe that the idea we propose and elaborate in this thesis can be a possible solution approach, that, at the moment, has been tested on an artificial benchmark.

In our setting and with our artificial data, we have learned that the location of the transportation requests, and thus also the pick-up and delivery sites has the highest impact in the calculation of the final bid of the 3PL on the bundle with those characteristics. Next comes the distance and then the volume characteristics of the bundle. With this in mind, we created an system that can rate a bundle and propose additional transportation requests to be added, via simulation phases. Location-based properties of bundles are, as we have seen, very important as it defines a degree of fruitfulness, generally defined as the presence of other shipments in the area. We have learned that using cluster techniques, this fruitfulness can be extracted.

We have also seen that when one learning system per 3PL’s preference is constructed, the amount of parameters to finetune, increases with the number of preferences one wishes to learn. This was the case in our statistical, on-line learning system, where each learning system consisted of 6 parameters, which can be manually adjusted. A solution to this problem was found by investigating other learning techniques, which do not suffer from finetuning a lot of parameters. More precisely, the applicability of neural networks is also examined in this thesis and is considered successful. The backpropagation algorithm, used inside the neural network to update the internal weights, did not require manual tweaking and in the end, was capable of providing results that were 4.1% better than in the on-line
setting. We believe this is one of the main reasons why the on-line system was beaten by the neural network.

Finally, we have also learned that it is important to make the solution approach for a particular problem to be as generic as possible and to notice the similarities with other optimisation problems. To test our work on a real-world setting, we have applied our ideas and techniques on a real-life problem instance of the School Bus Routing Problem. We have achieved similar results compared to other results on the SBRP benchmark, but with techniques that are much more flexible and distributed, which make the solution approach more applicable in a real-life situation.
Appendix A

Experimental configurations

Through the thesis, we have used every time the same configurations in the experimental results. For each of the configurations, we will denote the major details and explain the reasons behind them.

A.1 Configuration 1

In the first configuration, we used five 3PL companies, as it approaches a real-life setting where multiple 3PLs place bids into one auction house. Experiments with only two 3PL companies involved are too minimal to conduct good, representative tests. These companies are situated on the grid in square formation, as depicted in figure A.1.

![Figure A.1: Four 3PLs are located near the edges of the grid, while one 3PL is involved in the center.](image)

The instances of the Li and Lim benchmark used in this experiment are LC1101 upto LC11010. These 10 instances consist of the same 1000 locations, but with different PDP requests. In the graphs used in the experimental results, every day consists of averaging the results on all 10 benchmark instances. When 20 days are ran in the simulator, this means in fact that $20 \times 10 \times 1000$ PDP requests are
bundled and tested on their performance, which is significantly large. As denoted, multiple benchmark instances are used in the same experiment, as it is crucial that the underlying learner and bundling system is performing well on all instances, instead of learning an very good hypothesis on a single instance that is not applicable on other instance files. Results are averaged over these 10 instances over 10 runs or iterations to express the average behaviour of the learning system.

In short, the first configuration consists of the following details:

- Five 3PLs
- Square-formation
- Averaged over 10 instances

### A.2 Configuration 2

The second configuration is used to test the bundling aspects of the TRBS, when it comes to return shipments. To easily test this setting, we have created our own benchmark instance. This instance file consists of two groups of transportation requests, located, based on a Gaussian distribution, around points A and B respectively. Figure A.2 presents this setting. The volumes needed to transport were generated from a uniformly, random distribution between 10 and 100.

![Figure A.2: Two Gaussian distributions of PDP requests were used to create the benchmark instance. The departure and destination locations of the PDP requests are denoted in white and black dots, respectively.](image)
A.3 Previous work on School Bus Problem

Below are the results, obtained by Spasovic, on the SBRP in Riverdale, New Jersey. We use these results to compare our work.

<table>
<thead>
<tr>
<th>Bus</th>
<th>Route</th>
<th>Number of Stops</th>
<th>Number of Students</th>
<th>Vehicle Capacity</th>
<th>Capacity Utilization</th>
<th>Operating Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0-24-23-22-21-20-0</td>
<td>5</td>
<td>32</td>
<td>54</td>
<td>59.30%</td>
<td>$27.40</td>
</tr>
<tr>
<td>2</td>
<td>0-12-19-18-17-16-0</td>
<td>5</td>
<td>43</td>
<td>54</td>
<td>79.60%</td>
<td>$24.85</td>
</tr>
<tr>
<td>3</td>
<td>0-13-15-14-11-10-9-0</td>
<td>6</td>
<td>52</td>
<td>54</td>
<td>96.30%</td>
<td>$27.20</td>
</tr>
<tr>
<td>4</td>
<td>0-1-2-3-4-6-7-0</td>
<td>6</td>
<td>52</td>
<td>54</td>
<td>96.30%</td>
<td>$25.20</td>
</tr>
<tr>
<td>5</td>
<td>0-5-8-0</td>
<td>2</td>
<td>20</td>
<td>20</td>
<td>100.00%</td>
<td>$8.25</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>24</td>
<td>199</td>
<td>236</td>
<td>84.32%</td>
<td>$112.90</td>
</tr>
</tbody>
</table>

Table A.1: Results on the Heuristic Methodology on the School Bus Routing Problem of the elementary school of Riverdale, by Spasovic.
<table>
<thead>
<tr>
<th>Bus</th>
<th>Route</th>
<th>Number of Stops</th>
<th>Number of Students</th>
<th>Vehicle Capacity</th>
<th>Capacity Utilization</th>
<th>Operating Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0-24-23-22-21-19-20-0</td>
<td>6</td>
<td>32</td>
<td>54</td>
<td>74.10%</td>
<td>$29.59</td>
</tr>
<tr>
<td>2</td>
<td>0-10-18-16-17-0</td>
<td>4</td>
<td>43</td>
<td>54</td>
<td>64.80%</td>
<td>$20.95</td>
</tr>
<tr>
<td>3</td>
<td>0-9-15-13-12-11-14-0</td>
<td>6</td>
<td>52</td>
<td>54</td>
<td>96.30%</td>
<td>$26.74</td>
</tr>
<tr>
<td>4</td>
<td>0-1-2-3-8-5-7-0</td>
<td>6</td>
<td>52</td>
<td>54</td>
<td>96.30%</td>
<td>$24.17</td>
</tr>
<tr>
<td>5</td>
<td>0-4-6-0</td>
<td>2</td>
<td>20</td>
<td>20</td>
<td>100.00%</td>
<td>$8.07</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>24</td>
<td>199</td>
<td>236</td>
<td>84.32%</td>
<td>$109.50</td>
</tr>
</tbody>
</table>

Table A.2: Results on the ROUTER Methodology on the School Bus Routing Problem of the elementary school of Riverdale, by Spasovic.
<table>
<thead>
<tr>
<th>Bus</th>
<th>Route</th>
<th>Number of Stops</th>
<th>Number of Students</th>
<th>Vehicle Capacity</th>
<th>Capacity Utilization</th>
<th>Operating Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0-22-23-24-0</td>
<td>3</td>
<td>24</td>
<td>54</td>
<td>44.40%</td>
<td>$18.50</td>
</tr>
<tr>
<td>2</td>
<td>0-19-20-21-0</td>
<td>3</td>
<td>16</td>
<td>16</td>
<td>100.00%</td>
<td>$15.53</td>
</tr>
<tr>
<td>3</td>
<td>0-14-15-13-16-17-18-0</td>
<td>6</td>
<td>53</td>
<td>54</td>
<td>98.10%</td>
<td>$28.49</td>
</tr>
<tr>
<td>4</td>
<td>0-8-7-9-11-10-12-0</td>
<td>6</td>
<td>53</td>
<td>54</td>
<td>98.10%</td>
<td>$27.05</td>
</tr>
<tr>
<td>5</td>
<td>0-1-2-3-4-5-6-0</td>
<td>6</td>
<td>53</td>
<td>20</td>
<td>98.10%</td>
<td>$24.08</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>24</td>
<td>199</td>
<td>232</td>
<td>85.77%</td>
<td>$113.65</td>
</tr>
</tbody>
</table>

Table A.3: Results on the Sweep Methodology on the School Bus Routing Problem of the elementary school of Riverdale, by Spasovic.
Appendix B

Acronyms & abbreviations

- 3PL - Third-party logistics or also called carrier or transport companies. This company arranges the transport facilities and services to customers to make sure goods can be picked-up and delivered in time. A possible 3PL company in real life is UPS SCS\(^1\) or FedEx Supply Chain Services\(^2\).

- 4PL - Fourth-party logistics. In the SCM, this company provides coordination and planning for customers to address a wide range of 3PL companies to ensure a good price and a guarantee that all requests are assigned (to 3PL companies) at the end of the day. A possible company is Accenture\(^3\).

- A.I. - Artificial intelligence, a technique in computer sciences aiming to insert intelligence into machines or computers, called agents [Russell et al., 1996]. By perceiving its environment, an agent takes actions that maximize its chances of success to reach a global goal.

- DC - Distribution Center, or also called depot, this is typically one of the warehouses of the 3PL companies

- DiCoMas - Distributed Collaboration using Multi-agent System Architectures, a project, sponsored by the IWT, aimed to examine the possibilities of distributed collaboration. One of the application domains is SCM and transportation logistics.

- FTL - Full Truck Load, when a truck’s load is equal to its capacity, a 100% capacity utilization is achieved, then the truck is operating at full truck load. FTL specifications of all of a carrier’s trucks is the goal of the company

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\(^1\)http://www.ups-scs.com/
\(^2\)https://www.fedex.com/
\(^3\)http://www.accenture.com
as then the truck’s capacity is exploited to its maximum and the truck is running in optimal conditions.

- **LTL** - Less than Truck Load, when a truck’s load is less than its capacity, the truck is operating at less than truck load. LTL represents a suboptimal organisation or allocation of the truck’s capabilities and is not cost-efficient.

- **PDP** - Pick-up and delivery problems. A problem formulation in close relation to the vehicle routing problem that consists of several points on a map that serve as origin and destination locations for goods to be transported. The goal for a PDP-solver is to come up with an optimal route that covers all nodes. This, by taking into account possible additional constraints such as fuel efficiency, respecting driving hours, time windows and much more. The fact that in a vehicle routing problem formulation the destination of each transportation request is the central, fixed depot make of the VRP an easier problem than the PDP, which is more general problem formulation.

- **SBRP** - School Bus Routing Problem, an optimisation problem in close relation to the VRP. The problem formulation of the SBRP consist of routing students to the school, using several types of buses. The goal is to find the optimal assignment of buses to bus stops, while taking into account efficiency, effectiveness and equity.

- **SCM** - Supply-Chain Management, a relatively new way of working for companies to create goods, aiming to create independent compartments, each with their own goal, by eliminating unnecessary dependencies in a company by adding more aspects of coordination.

- **VRP** - Vehicle Routing Problem, a combinatorial optimisation problem seeking to service a number of customers with a fleet of vehicles. VRP is an important problem in the fields of transportation, distribution and logistics. Thus, the problem consists of a series of customers, each with a certain demand, that wish to see this demand transported towards a fixed, central depot. The goal is to find an optimal and minimal allocation of the transportation equipment needed to cover these demands, in order to reduce costs.
Bibliography


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