PRICING DECISIONS BY FREIGHT FORWARDERS

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

Qin Han

QIN HAN

30 June 2015

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SUMMARY

As logistics service providers, freight forwarders (FFs) are intermediary parties who connect shippers (SPs) to carriers (Cs) in the logistics chain. The focus of this research is on non-vessel operating common carriers (NVOCCs) - FFs who do not own any vessel but make use of the capacity and shipping network of carriers to move cargo on behalf of shippers. Their profits come from the price difference between the contract price received from shippers and that paid to carriers.

The purpose of this research is to assist a FF with its pricing decision. In the first phase of the research, a game theoretic (GT) approach is proposed to investigate how a FF could formulate its optimal pricing decision in face of competition when it has complete information of the entire system. The potential reactions from other parties (shippers and carriers) and the competition from other FFs are taken into account. Pricing decisions by the FF are investigated in a situation involving shippers, FFs, and carriers. The approach takes into account: 1) shippers' selection behavior; 2) the potential reactions from competing FFs; and 3) the best combination of available capacity from carriers.

In the second phase of the research, learning mechanisms are proposed to assist a FF to adapt its pricing decisions over time when it has limited information of the entire system. A Multi-Agent System (MAS) is built to

investigate the interaction between the three parties so that the performance of each learning approach can be examined. Multi-agent simulations are conducted to investigate the interactions under various combinations of FFs that learn. The purpose of conducting the simulation is to investigate whether learning from previous transactions can lead to better freight pricing decisions for the FF. Which is the best learning mechanism, and how learning and pricing performance can be optimized are also questions this research would like to answer. The critical parameters that determine learning performance as well as the best setting for parameters are investigated as well.

The third phase of the research aims to help a FF formulate its best pricing decisions based on the information that is accessible to it in the real world operations. All the information the FF uses to can be obtain in the reality. The FF uses its internal information (goals, profit gain or loss, market share gain or loss, or quotations are accepted or not) and external information to update its pricing decisions over time. Multi-agent simulations are conducted to investigate the pricing performance of various learning models under various pricing situations. The critical parameters that determine learning performance as well as the best settings for these parameters are investigated as well. The scenario when there is a short period of under supply is also examined.

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LIST OF SYMBOLS

- Δ_n: the difference between the estimates of $Q(s_n, a_n)$ at two different times
- CA_j: available capacity of C_j
- CUC_i: consolidated per unit cargo movement cost of FF_i
- C_j: a specific carrier j
- FF_i: a specific freight forwarder i
- PD_i: pricing decision of FF_i
- P_l: the probability for scenario l to occur
- $R_j(x)$: the unit cargo charge with respect to a cargo volume of x;
- SF_k: a self-fulfillment shipper k
- SP_k: a specific shipper k
- TV_i: total volume of cargo received by FF_i in subgame 2
- U_{ki}: the utility SP_k will perceive when selecting FF_i
- V_k: the volume of cargo SP_k would like to transport
- $V^{\pi}(s_t)$: a discounted reward which quantifies the performance of a decision π starting at state s_t
- ag_i: FF_i's aggressiveness associated with its pricing decisions
- a_j: a parameter associated with C_j's freight rate scheme, which represents the carrier's marginal cost

- a_n: the action taken at time step t
- ap_i: the unit of markup adjustment by a FF_i
- b_j: a parameter associated with C_j's freight rate scheme, which affects the profit distribution between carriers
- cv_{li}: the amount of cargo FF_i obtains in scenario l
- d_i: a parameter associated with FF_i, which affects its optimal cargo split
- k_a: an action a has been chosen k_a times prior to time n (action-value method)
- p_a: the probability for an action a to be chosen (Softmax method)
- p_{ki}: the probability for shipper k to choose FF_i
- pr_i: the desired markup of FF_i
- r_t: the reward a player earned at time t
- s_t: a state to describe the world at time t
- v_{ki}: the systematic (representative or deterministic) component of U_{ki}
- $x_{\underline{i}j}$: the volume of cargo C_j has already accepted from the other $FF_{\underline{i}}$
- x_{ij}: the volume of cargo FF_i intends to offer to C_j
- x_{ij}^l: the amount of cargo FF_i offers to C_j in scenario l
- z_{li}: the average unit cost for FF_i in scenario l
- α_k: a positive constant associated with SP_k's tastes when selecting a preferred FF
- β_k: SP_k's sensitivity towards price

- ε_{ki}: the random part (disturbances or random components) of U_{ki}
- $E(TP_i)$: the expected total profit of FF_i
- F: the fixed cost
- M: a parameter affecting the optimal cargo split of FFs
- N: the total analysis period
- P: the unit cargo movement charge
- $Q(a)$: the evaluation of an action a
- $Q(s, a)$: the evaluation of an action a carried in state s
- Q: the volume of cargo offered by shippers
- TP: the profit equation of a freight forwarding company
- w: the cost to move one unit of cargo
- b: an arbitrary action within the action apace $\mathcal{A}$
- l: a possible scenario FF_i face in sub-game 1
- n: a specific analysis period
- $\mathcal{A}$: an abstraction of the possible actions
- $\mathcal{S}$: an abstraction of the actual possible states of the world
- α: the step-size parameter for TD-learning
- γ: discount factor
- $\delta(s_n, a_n)$: the state transition function which defines how the action a_n taken in state s_n will lead to a new state
- ε: the greedy parameter (action-value method)

- πF_i: the total cargo movement costs to FF_i.
- π: the decision of a player which is a mapping from state to actions
- τ: the temperature parameter associated with Softmax method

CHAPTER 1 INTRODUCTION

1.1 Introduction

Freight forwarders (FFs) face various decisions related to operations management in their daily work when facing shippers (SPs) and carriers (Cs). Among them, pricing is the process of determining what must be provided by a customer in return for a product or service (Schindler, 2012). A FF's pricing decision determines the price for its logistics service. In this regard, a pricing decision pertains to the unit cargo movement fees the FF charges a shipper (Fig. 1.1). Each pricing decision can be represented on a pricing curve, with the horizontal axis indicating the volume of cargo and the vertical axis corresponding to the unit cargo charge. The shape of the curve distinguishes one pricing decision from another. In this research, helping FFs make pricing decisions is the same as helping them determine their pricing curve. As shippers can go to FFs or directly to carriers for this shipping service, a smart FF needs to determine and adjust this pricing curve so as to compete with other FFs and carriers. FFs may do so for the reason of pursuing profitability or market share in a highly competitive logistics market. They need to be clear about the basis of their pricing decisions, their objectives, and the potential reactions and decision-making behavior of the other parties involved.

When contacted by shippers for logistics services, FFs quote charges based on pricing decisions regarding their services. A superior pricing decision aims to price as profitably as possible by capturing more value; however the potential reactions of other parties and competitors limit the level of price (or markup) attainable.

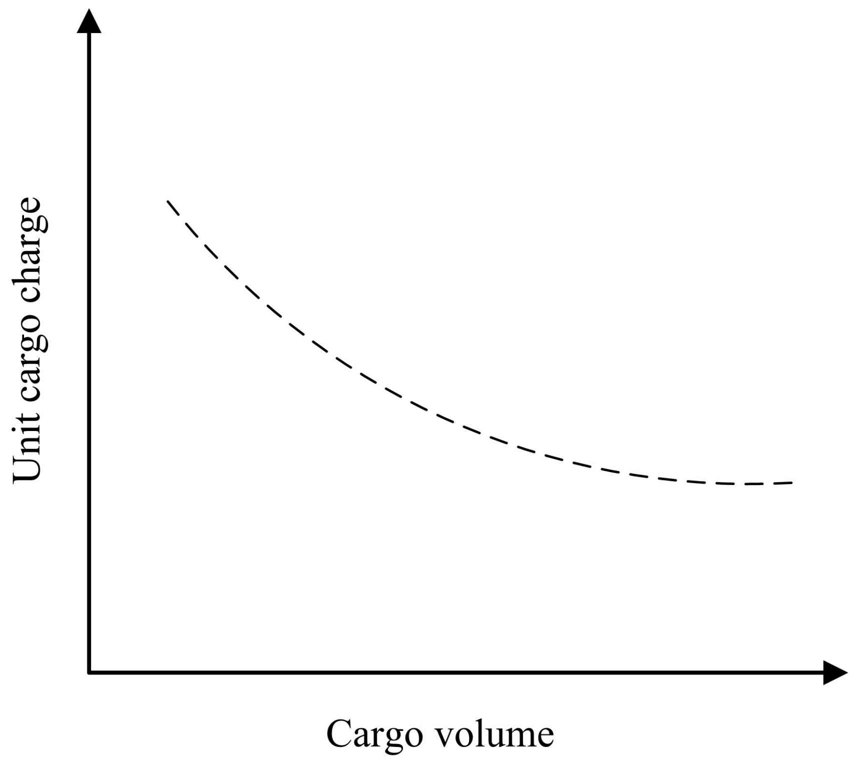

Fig. 1.1 Pricing decision of FFs

Although a shipper can go directly to a carrier, there are good reasons why a shipper might want to outsource to a FF the design of a cargo movement plan, as well as the subsequent monitoring and execution of the plan by carriers.

First, a FF can guarantee demand, space, and level of service (speed, economy, and safety) (Burkovskis, 2008). Shippers are mainly concerned about whether cargo can be moved from an origin to a destination in a timely manner, at an acceptable cost and with a required level of service. Shippers can also acquire door-to-door delivery (Y. Li et al., 2009), get rid of unnecessary services and additional functions (e.g. transportation, physical distribution of goods, and storage) that are not considered core business for a company. Second, shippers are able to make use of a mixture of different transportation modes with lower transportation cost through FFs (Y. Li et al., 2009). In most cases, carriers (airlines or shipping lines) own large capacities for a limited number of destinations, while FFs are able to offer more flexible origin-destination pairs with access to greater aggregated capacities. Thus specialized third party logistics companies can offer competent, reliable, and effective industrial logistics services. Because of this, shippers are able to take advantage of economies of scale obtained by FFs from carriers and insurance companies even though they may only have relatively small amounts of cargo to ship (Burkovskis, 2008). Furthermore, shippers eliminate the cost of organizing cargo transport themselves.

There are two main concerns when FFs make pricing decisions: 1) how to balance price and volume in order to maximize profit given the cost of cargo movement; 2) how to transport received cargo in the most cost-effective manner so that a given level of service can be expected given the contracts signed with shippers. This research focuses on these two concerns when formulating the pricing decisions by FFs so that profitability can be assured. The total profit (TP) of FFs comes from the price difference between the contract price received from shippers and that paid to carriers, and can be defined as:

$$TP = Q(P - w) - F \tag{1.1}$$

Where Q denotes the volume of cargo offered by shippers; P denotes the unit cargo movement charge – pricing decision; w denotes the cost to move one unit of cargo; F denotes the fixed cost. The focus of this research is on non vessel operating common carriers (NVOCCs). For a NVOCC, w can be estimated based on tariff schemes of carriers. The fixed cost F is due to the overhead of daily operations and management, labor cost, and other costs related to infrastructure (rental for offices, equipment, etc.). As articulated by Yin and Kim (2012), FFs offer shippers logistics services which can be considered as news-vendor type products. FFs, like "newsvendors", buy slots from carriers and sell them to shippers, which makes the services provided by FFs look like "newspaper delivering service": once a particular voyage is undertaken, all unutilized slots on board are wasted and cannot be stored.

Good pricing decisions allow FFs to offer shippers more attractive logistics services, as well as remain competitive over other third party logistics companies. In a highly competitive market, FFs need to make good pricing decisions on their charges to shippers. As a party in the middle of the chain of transactions, FFs take into account the pricing decisions by other FFs and carriers, and the likely decision making behavior of shippers. In order to attract cargo from shippers, FFs compete on price and level of service. FFs should propose charges and cargo movement plans by: 1) referring to upstream information from shippers (amount of cargo and shippers' requirements); 2) downstream information from carriers (tariff scheme, capacity, and schedule of available carriers); and 3) the information about other competing FFs. Learning from previous transactions should be incorporated as well so that the performance of previous decisions can be evaluated and future decisions can be improved. Pricing decisions are then not one-time static decisions but iterated over multiple transactions. A good pricing decision should also be made in a strategic manner, meaning that a FF should price its service more profitably by capturing more value, not necessarily by making more sales but undermining profitability.

1.2 Interaction between SPs, FFs, and Cs

FFs are the middle men who facilitate the interaction between shippers and carriers. Shippers have two alternatives when they want to move cargo from an origin to a destination: 1) contract the work to one FF (outsourcing shipper); or 2) design their own cargo movement plan, and contract with carriers to implement it (self-fulfillment shipper). Cost, level of service, and timing are the key concerns of shippers. When shippers have cargo to be transported, they announce the volume of cargo and requirements to FFs. Each FF then quotes proposed charges and submits a cargo movement plan based on its pricing decision. Shippers decide on which is the better alternative after receiving the responses from FFs. If a FF is used, the FF needs to further split the cargo received among carriers based on the shippers' requirements and the carriers' schedule and freight rate. Similarly, self-fulfillment shippers also have to consider a cargo split among the carriers. Carriers decide on which FFs to serve and whether to adjust their pricing scheme and capacity.

The relationship between different entities will also affect how the interaction between these entities takes place. Carriers are the parties which move cargo physically within a transportation network using trucks, vessels, and shuttle trains. They want to maximize their own goals, taking into account competition from other carriers as well as cargo business from FFs and shippers directly. As a man-in-the-middle, a FF can be either a collaborator or a competitor for the business of a carrier. FFs work as intermediaries that benefit by sharing part of the revenue that should have belonged wholly to carriers. Carriers still have an incentive to work with FFs, as the latter can assure carriers of a large amount of cargo. By working with FFs, a carrier may also be able to receive more cargo volume compared to working on its own.

A general conceptual framework representing the real world interaction and information exchange between the three parties is proposed in Fig. 1.2. The framework shows the flow of actions starting from the generation of shippers' demand till the cargo movement by carriers. The purpose of proposing the framework is to ensure that the key elements of the three-tier interaction are captured, including critical features whilst omitting unnecessary details. The interaction between shippers, FFs, and carriers can therefore be modeled properly in the following chapters.

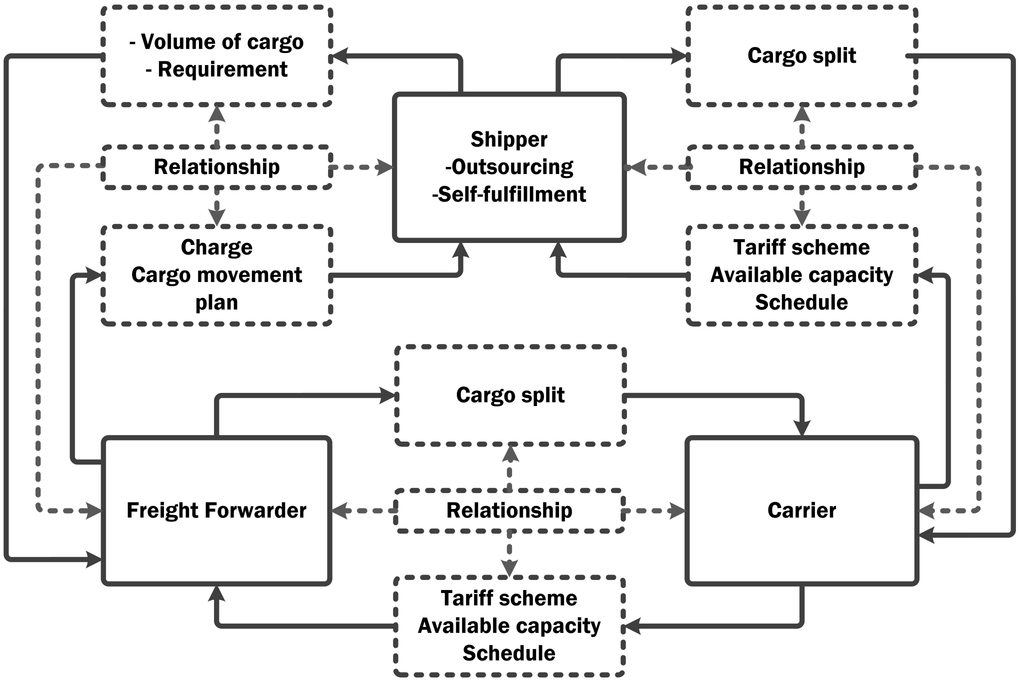

Fig. 1.2 Real world interaction between shippers, FFs and carriers

1.3 Research Motivation

Past research on FFs relevant to this study can be categorized into four main streams: (a) shipment decision problems: shipment integration and consolidation (Huang & Chi, 2007), routing (Cheung & Hang, 2003), infrastructure choice (Tongzon, 2009), logistics service network design (Creazza et al., 2010), and loading (Y. Li et al., 2009); (b) capacity management problems: either long term (Amaruchkul & Lorchirachoonkul, 2011) or short term (Jaržemskis, 2005) allotment booking and planning; (c) interaction with other parties - carrier (Yin & Kim, 2012), shipper (Rau et al., 2006)), or collaboration (Krajewska & Kopfer, 2006) and coordination (Reinheimer & Bodendorf, 1999) with other actors; and (d) behavior research: factors that affect a customer's choice of preferred third party logistics service provider (Wen et al., 2011), FFs' choice between different transportation modes (Feo et al., 2011), or other decision making issues that affect FFs (C. S. Lu & Marlow, 1999). Although there has been an increasing amount of literature on FF decision making and operations management, very little has addressed the issue of pricing with an objective of assuring profitability.

Many of the models defined in the research literature are conceived from a single perspective, or from the perspective of a unified system where the potential reactions of stakeholders and component entities are considered as constraints or simply omitted (characterized by system optimality and centralized decision making). However, in reality shippers, FFs, and carriers can pursue their own goals (characterized by user equilibrium and decentralized decision making). They can consider tradeoffs but do not need to sacrifice benefits for the achievement of system optimality. Conflict or congruence between the goals of different participants brings about competition or cooperation, and the decisions made by the different parties will change accordingly. What will pricing decisions be if each stakeholder is free to pursue its own goals and individual goals need not be subordinated to an overall global objective?

Most of the previous research focuses on optimizing the decision of FF only with respect to current information. Learning and feedback from previous transactions are not taken into account. However, in a highly competitive market, FFs can improve their pricing performance by adapting their decisions vis-à-vis their competitors. These decisions should be sensitive to the changes in the market as well as the decisions made by other actors. Will pricing performance be improved through learning and feedback?

Much of the literature assumes homogeneity in the profile of stakeholders – it is difficult to formulate analytical models that account for different objectives, competition and learning strategies among actors in a system. How will individual and system performance be affected if profiles of stakeholders are allowed to be different? Will the outcome and behavior of the system that emerge out of the interaction between components of a competitive system be different from one where all parts of the system are subordinated to a global objective?

1.4 Research Scope

The aim of this research is to develop pricing decisions for FFs in an oversupply market by incorporating: 1) the potential reactions from other parties (shippers and carriers) and competing FFs; 2) the learning through feedback information from past transactions; 3) the interaction between competing FFs with different pricing decision making mechanisms.

In the first phase of the research (Chapter 3), a game theoretic (GT) approach is proposed to investigate how a FF could formulate its pricing decision in face of competition when it has complete information of the entire system. The market is assumed oversupplied, and the above GT approach takes into account the price preference of shippers and the competition from other FFs. The GT approach formulates a FF's interaction with shipper and carrier as a three-level extensive form game; this new formulation extends the previous two-level formulation of logistics problems using game theory. This adds more complexity but potentially yields new insights as more interdependent decisions are included. The problem is formulated in a decentralized manner, with each party pursuing its own objective unilaterally but taking into account the competitive actions of other parties. Individual objectives are not subordinated to an overall objective by using weighted criteria. The decisions that emerge out of the individual interactions are more realistic. Under equilibrium conditions, each player reaches its optimal decision and no one has the incentive to deviate unilaterally in order to improve its outcome. The model formulation emphasizes profit maximization rather than just cost reduction or revenue maximization. As a FF's profit is the difference between costs (paid to carriers) and revenue (earned from shippers), FFs have to balance costs and revenue objectives in the face of volume preference from carriers and price sensitivity from shippers. This approach also provides FFs pricing decision support in the determination of a reference price to attract business from shippers and compete with other FFs. This reference price can be used as a benchmark to examine the pricing performance of other pricing decision models.

In the second phase of the research (Chapter 4), learning mechanisms are proposed to assist a FF to adapt its pricing decisions over time when it has only limited information of the entire system. Including the effect of learning allows the study of the system as it evolves and adapts, instead of only the results in the final state at equilibrium. In this way, the feedback from previous transactions can be incorporated. The work reported in this thesis investigates the question of whether learning from previous transactions can lead to better freight pricing decisions for FFs. By adapting pricing decisions over time, FFs can improve their future decisions by examining the responses from other participants and how these responses affect them. A FF capable of learning responds to stimuli from its environment and adjusts the way it performs tasks through trial and error - similar to the way humans learn. The RL mechanisms proposed in this research are suitable for complex tasks that resist attempts to encode them as programs, and can be used even when no training data is available (Ertel, 2011). In RL, the preference for actions that bring rewards is reinforced, whilst that for actions that lead to loss is weakened. It does not require complex formulation and a lot of historical data - it works with only current (online) information. RL also does not require complete information of the entire system. This is suitable for the situation where FFs need to make pricing decisions even though they may have only very limited information. They can only refer to their own internal information (gain/loss of profit and increase/decrease of market share) and some external information (cargo volume and requirements announced by shippers, the acceptance/rejection of cargo movement plans and quoted charges, and whether more shippers need freight forwarding services).

In the third phase of the research (Chapter 5), the aim is to help a FF formulate its best pricing decisions only given the information that is accessible to the FF in real world operations. The FF uses its internal information (goals, profit gain or loss, or market share gain or loss) and external information to update its pricing decisions over time. The following scenarios are also examined: 1) there is a short period of under supply; 2) demand and supply are allowed to vary; 3) activities can occur at any time.

A Multi-Agent System (MAS) is also built to investigate the interaction between shippers, FFs and carriers so that the performance of each learning approach can be examined under various scenarios (Chapter 4 and Chapter 5). The MAS implementation allows experimentation with a system of interacting agents representing shippers, FFs, and carriers. Multi-agent simulations enable the study of the effect of competition between FFs with different learning strategies. The activities in the logistics market are conducted via interactions between different actors. The manner in which these interactions take place will affect the decisions made by each participant and the outcomes obtained. By building a MAS, the behavior of a complex system is reproduced by the interaction of simple rules that govern the response of the actors in the complex system. Slight changes in interaction rules and behaviors of a single entity, when instantiated in many local contexts, may lead to changes of system behavior. A MAS does not require complex formulation; instead, it works with simple rules that are easily customized. The MAS system can be easily adapted to include more problem variables and interactions between problem variables - this allows differentiation in the details of pricing and learning mechanisms between actors in the research. A MAS can investigate the interaction when each actor has its own behavior through having different decision model structure and parameters. The interaction between different combinations of actors can also be experimented with, and the system behavior that emerges out of simulations will be more realistic and meaningful. Furthermore, different decision making approaches and the setting of parameters can be examined over time by conducting multi-agent simulations. Simulations of the real world situation enable this research to support FFs in their pricing decision. The pricing decisions are no longer one time decisions but are decisions that are adapted over iterated transactions. Multi-agent simulations are also conducted to investigate the interactions between various combinations of FFs that learn.

1.5 Thesis Outline

Chapter 1 presents background, motivation, research scope and objective. Chapter 2 reviews past research that is related to this study. Chapter 3 describes a game theoretic (GT) approach for pricing decisions by a FF when the FF has complete information of the entire system. Chapter 4 proposes to incorporate the effect of learning from past transactions in a FF's pricing decisions when the FF only has limited information of the entire system. A multi-agent system is built involving shippers, FFs, and carriers. The results of multi-agent simulations under various scenarios is presented as well. Chapter 5 examines the pricing decision of a FF based on the information that is accessible to him in the real world operations. Multi-agent simulations are conducted by extending the multi-agent system built in Chapter 4 . Chapter 6 concludes and summarizes the whole research.

CHAPTER 2 LITERATURE REVIEW

2.1 Decision Making Models for FFs

Existing research on FF decision making and operations management problems can be categorized into four main streams.

The first stream of research focuses on various operations and management related issues: shipment integration and consolidation (Huang & Chi, 2007), routing and scheduling (Cheung & Hang, 2003), infrastructure choice (Gardiner et al., 2005; Tongzon, 2009) (Tongzon, 2009), logistics service network design (Creazza et al., 2010), or loading (Y. Li et al., 2009). Shipment scheduling and routing problems focus on the determination of an optimal route to transport cargo from an origin to a destination using links in a logistics service network. FFs need to determine the time to collect cargo from shippers, the route on which cargo is transported, and intermediate stops for the cargo. Several authors combined the standard shipment scheduling and routing problem with backhaul and time window constraints (Cheung & Hang, 2003), or with cargo integration and consolidation (Krajewska & Kopfer, 2009; Moccia et al., 2011; Uster & Agrahari, 2010). Azadian et al. (2012) investigated the movement of time sensitive air-cargo with respect to real-time and historical information (flight availability, departure delays, and arrival times). In order to make use of economy of scale and acquire quantity discounts from carriers, FFs consolidate individual consignments to make up a full container load at the origin. This arrangement allows small volumes of cargo from different shippers but with the same origin and destination to be transported together so as to offer greater security at lower shipping cost. At the destination, the consolidated cargo is deconsolidated back into original individual consignments and delivered to respective consignees. A lot of research has been conducted on shipment consolidation and integration. Huang and Chi (2007) considered air FFs' consolidation problem. Wong et al. (2009) investigated shipment integration and consolidation together with FF's in-house capacity as well as the available capacity of its partners and sub-contractors. Leung et al. (2009) examined the optimal integrations and consolidations of air cargo shipments given a number of jobs and processing units. Z. Li et al. (2012) worked on an unsplittable shipment consolidation problem of an air FF. Bock (2010) used a new real-time-oriented control approach to expand load consolidation, reduce empty vehicle trips, and handle dynamic disturbances by considering vehicle breakdowns or deceleration of vehicles, traffic congestion, street blockages as well as dynamic incoming transportation requests.

The second stream of research focuses on the planning and management of freight capacity. As NVOCCs do not own any vessels, they need to send all the cargo received from shippers onwards to carriers. The demand from shippers may vary, and FFs have to decide whether they should book capacity from carriers in advance so as to get a discounted freight rate and secure space from carriers in anticipation of getting the business from shippers. Booking too much space beyond the actual demand will incur extra cost, whilst a lack of space may lead to the loss of business opportunities from shippers. Liu et al. (2009) state that FFs and carriers should establish a cooperative relationship and form virtual enterprise alliances (VEA) directed by contracts. On the other hand, carriers sell (or presell) their services to intermediaries (FFs) instead of directly to the real shippers (Yin & Kim, 2012). This builds their relationship with the FFs. As the service provided by carriers is also newsvendor-like and cannot be stored, FFs may consider two kinds of purchases from carriers: long-term contracts and free sale (short term purchase) (Jaržemskis, 2005). This will affect the choice of preferred carriers and the cargo split among carriers by a FF. It will also influence the behavior of carriers when they adjust their tariff scheme and decide on the amount of guaranteed capacity for a particular FF. For sustainable development in a competitive business market, a carrier cannot design its freight tariff merely considering its own profit. A reasonable profit sharing mechanism should be considered. Some researchers view the relationship between FFs and carriers as a kind of game, in which carriers are rule makers whilst FFs serve as newsvendor-type followers (Yin & Kim, 2012). This gives rise to a 'partner selection problem', which brings new perspectives on how FFs evaluate and select partner carriers to work together (Brookes & Altinay, 2011; Ip et al., 2003; Pidduck, 2006; Solesvik & Encheva, 2010).

The third type of research examines the interactions between FFs and other parties. Yin and Kim (2012) examined the FF-carrier interaction by considering how container lines should set their freight tariff so as to maximize expected profit. The authors also discussed how the behavior of FFs (in terms of changes in order quantities) would influence the decisions of carriers (in terms of the tariff scheme). Liu et al. (2009) examined FF-carrier interaction to help FFs select carriers based on decision theory and game theory. Rau et al. (2006) considered the negotiations between shipper and FF on unit shipping price, delay penalty, due date, and shipping quantity using a learning-based approach. Shipper and carrier interaction was also examined in the same article. In order to survive in a highly competitive market, some FFs seek opportunities for cooperation or collaboration with other independent FFs (Krajewska & Kopfer, 2006). Coordination between shippers, FFs and carriers (coordination in the vertical dimension) may also bring about win-win scenarios for each of these parties. Reinheimer and Bodendorf (1999) considered market orientation coordination in the air freight forwarding industry by applying easily accessible communication infrastructures as well as investigating qualitative aspects in price-finding mechanisms.

Research on the behavior of FFs comprises the fourth main stream. This kind of research examines the behavior of FFs when they do business and make decisions. The reasons behind these behaviors and behavioral patterns are also included. C. S. Lu and Marlow (1999) explored the strategic differences between shipping companies, shipping agencies, and ocean FFs by classifying them into four strategic groups based on the key strategic factors obtained from factor analysis. As FFs are usually considered to be utility maximizers, Z. Li and Hensher (2012) reviewed all past freight behavior studies using Random Utility Maximization (RUM) and proposed an alternative behavioral paradigm – Rank-Dependent Utility Theory (RDUT) model to incorporate the risk-taking attitudes of transporters and shippers rather than the previous risk-neutral assumption. To study the effectiveness of freight transport policy, Feo et al. (2011) modeled the modal choice between door-to-door road transport and short sea shipping available to FFs. Their work identified the critical areas that should be addressed by future policy action. Some researchers also investigated the decision-making behavior of FFs with respect to: 1) the location selection by third party logistics service providers (Shiau et al., 2011); 2) the comparison and selection among various alternatives taking into account economic, environmental and social sustainability (Simongáti, 2010); 3) logistics service network design (Creazza et al., 2010; Lin & Liang, 2011). Burkovskis (2008) discussed ways in which a FF effectively participate in the transportation process and proposed rules to examine investments in developing freight forwarding services. Yang (2012) examined the relationship between the ability to innovate by ocean FFs and firm performance. Four critical logistics service qualities/capabilities were identified: logistics service reliability, logistics value-added service, flexibility, and logistics information services. Cheng and Yeh (2007) examined internal and external factors that affect the sustainable competitive advantage (SCA) of an air-cargo FF. G. S. Liang et al. (2006)

identified the link between service management requirements and customer needs for an ocean FF by characterizing customer needs by their importance, levels of satisfaction, and the service management. Ducruet and van der Horst (2009) verified the role of intermediaries in the transport integration by considering the relationship between transport integration and port performance. Markides and Holweg (2006) discussed the diversification of services and activities by FFs in the UK. Suggestions that would help FF gain more business from shippers was offered in the research conducted by Wen et al. (2011).

2.2 Pricing Decisions

Pricing decisions are the decisions made by sellers or service providers on the price for a product or service after examining a multitude of factors such as competition, cost, advertising, and sales promotion (AllBusiness, 2015). A reasonable price for a product or service is not a single number but rather a range of feasible price points.

Various research has been done on carriers pricing decisions. Chi and Koo (2009) examines the pricing behaviors of United States air carriers in domestic markets. Mozafari and Karimi (2011) studies pricing and fleet management decisions for full-truckload freight carriers, which compete on a road network. Mutlu and Çetinkaya (2013) studies a carrier–retailer channel and examine the profitability of the centralized and decentralized channels under price-sensitive demand. Toptal and Bingöl (2011) studies the transportation pricing problem of a truckload carrier in a setting that consists of a retailer, a truckload carrier and a less than truckload carrier. Yin and Kim (2012) characterize freight rate tafiff freight tariff by price-break points, discounted freight rates, and penalties for unsold space. Xu et al. (2010) examines how the loss averse effect of downstream customer can affect the decision of carrier to maximize its profit through contract price one carrier , one forwarder and a downstream customer market. However, not much existing research has been done to address the pricing decision of FFs.

Section 2.2.1 discusses how a FF can identify a range of price points using the exchange value method. FFs aim to capture more profit through price but price and demand are interrelated. This issue is discussed in Section 2.2.2.

2.2.1 Price Boundaries

According to Smith (2012) and Nagle et al. (2011), price is the value that a firm captures in a mutually beneficial exchange with its customers. The right price is often not a single number but rather a range of potential points (Zone of Potential Agreements, ZOPA) that benefits both customers and the firm. Based on the exchange value method, FFs could identify a reasonable price interval within which they could choose a value as the price of their services, and narrow pricing discussions to a reasonable range of price points.

As shown in Fig. 2.1, two types of boundaries can be identified for a product or service - extreme boundaries and narrower boundaries. The extreme boundaries define a range of acceptable prices outside which no rational buyer or seller would ever transact. The upper and lower bounds of extreme boundaries are determined by the full consumer utility and the marginal cost to produce. The narrower boundaries, which lie within these extremes, define a range of prices that are most likely to encourage customer transactions and leave the firm in the most favorable position. The upper and lower bounds of the narrower boundaries are determined by the exchange value and inferior alternatives. The full consumer utility is the value a costumer gains from having the product. The marginal cost to produce is the cost to produce one more unit of output. The exchange value of a product is the price of the nearest comparable alternative adjusted for the differential value of the product. The comparable alternatives are the solutions with which customers can accomplish the same or a similar set of goals. The differential value is defined as the change in customer utility that a product delivers in comparison to the alternative (exchange value = price of comparable alternative + differential value). The inferior alternatives are competing alternatives that deliver similar benefits to the one under consideration with less overall customer utility. People usually have heightened sensitivity in relation to their point of reference (Smith, 2012) - the reference price. The last price they paid for a product, the price they currently see or last saw on a product form consumers' reference price for a given product. All the definitions and price points mentioned above determine the feasible price range of a product or service.

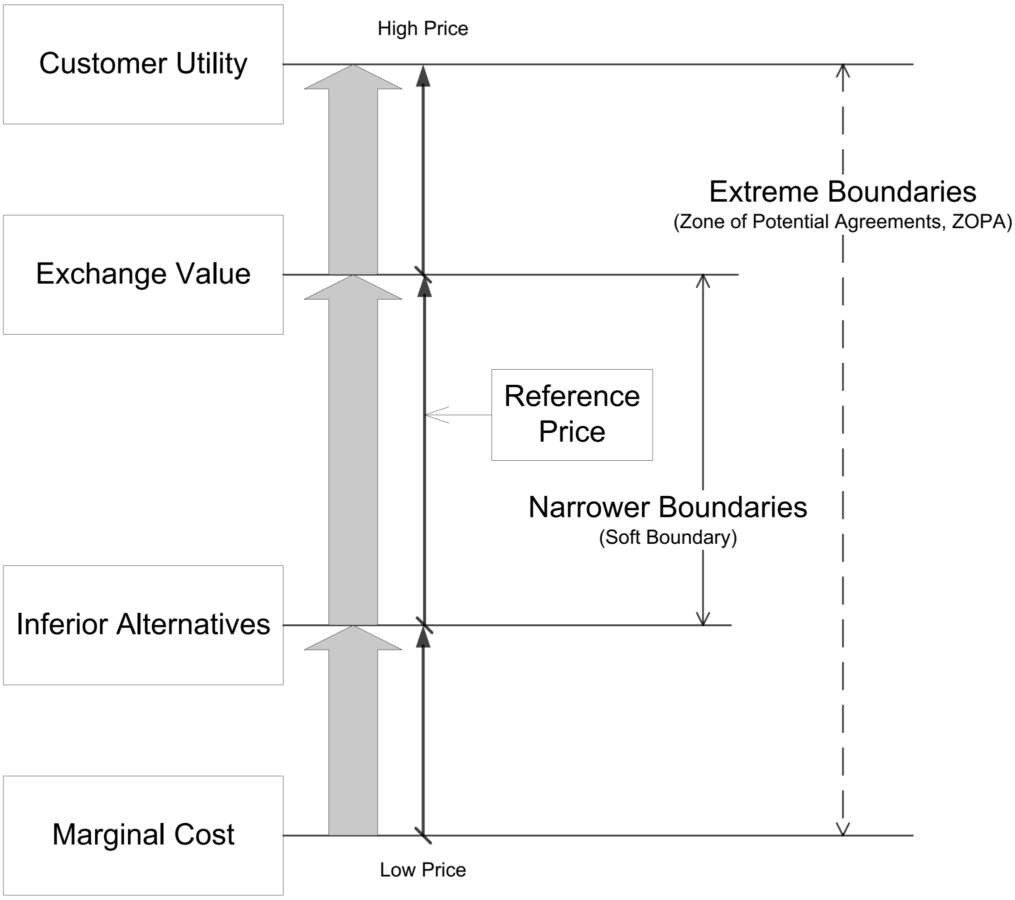

Fig. 2.1 Price boundaries for a product or service

2.2.2 Price Elasticity of Demand

In order to make pricing decisions in a strategic manner by capturing more profit, FFs should know how price changes will affect the demand they are facing. This issue can be investigated by using the concept of price elasticity of demand. Price elasticity of demand is a measure of how much the quantity demanded of a good responds to a change in the price of that good. It is computed as the percentage change in quantity demanded divided by the percentage change in price (Mankiw, 2012). Price elasticity of demand reflects how willing consumers are to buy less of the good as its price rises. According to Smith (2012), a market is considered to be elastic when a small change in price has a large effect on the quantity sold; whilst a market is considered to be inelastic when a large change in price has only a small effect on the quantity sold. In the short run, an elastic market tends to favor price cuts to improve profitability, whilst an inelastic market tends to favor price increases to improve profitability. The firm-level elasticity of demand is usually greater than or equal to that at the industry level.

The demand for freight transport is determined by demand for physical commodities in a given location, which is a derived demand arising from customers demand for certain products (Lun et al., 2010). At the industry level, FFs face an inelastic market, in which the demand of cargo movement depends on the production of manufacturers, the need of end market consumers, and the global economic condition rather than the market freight rate. It is because the total volume of cargo movement is not highly correlated with the freight rate, but depends on the externalities beyond the shipping or freight industry. Shippers always have cargo at hand to be transported from an origin to a destination. As long as they can find cost-effective ways to do so, they will transport the cargo anyway. However, changes of freight rate will have indirect effects on the demand of cargo movement. It is because freight rate will affect the magnitude of a product's sale price and its manufacturer's cost. Finally, the need of the product in the market is affected, and the total demand for the movement of this product is affected.

At the firm level, FFs face a relatively more elastic market. Major customers with regular and large demand of cargo movement only consider price as one of the key issues before signing a contract with a logistics company. For example, an automobile manufacturer may also be concerned about the level of service, reliability, and timing; therefore they will have a higher willingness to pay for more reliable and higher level of service. For the military cargo, shippers may highlight timing and reliability over other issues related to price or cost. These shippers may also consider previous interactions, and thus are willing to pay more as long as they are satisfied with previous experiences. On the other hand, for medium or small customers, they are more sensitive towards cost, and thus have less willingness to pay. If switching to another company could reduce their expenditure, they usually have no incentive to stick to the previous company. Many logistics company have noticed their major customers to be more stable and loyal, whilst their medium and small customers switch service providers very quickly.

This diversity of the behavior pattern between major customers and medium/small customers present FFs the incentive to price segment their services in a profit-driven manner. Profit-driven pricing means that a company evaluates its success at price management by the profit it generates, rather than by customer-driven, share-driven, or even cost-driven pricing. When interacting with major clients or someone who is not sensitive to the price, FFs should make pricing decisions on a case-by-case basis: trying to balance price, level of service and other personalized requirements while guaranteeing the profit. On the other hand, when interacting with smaller clients or customers who are sensitive to price, FFs should try to attract them with better prices and an acceptable level of service to compete with other service providers.

2.3 Game Theory (GT)

Game theory (GT) offers a valuable economic and mathematical tool to solve the decision-making problem in an environment where each decision-maker's actions interact with those of others (Geckil & Anderson, 2010). It is a theory which accounts for both independent and interdependent decision making (Kelly, 2003) and thus fits the needs of this research. Game theory offers FFs the potential to take into account the possible reactions and decision-making behaviors of other parties including competing FFs. It aims to find optimal solutions to situations involving conflict or cooperation, under the assumption that players are instrumentally rational and act in their own best interests (Kelly, 2003).

We would like to examine FFs' decision-making in a "game theoretic environment" because the outcome for each individual is affected not only by its or her own actions but also by the actions of others (Hargreaves-Heap & Varoufakis, 2004). In this way, the interaction between the players can be modeled in a mathematical way with the purpose of helping the decision maker make its decisions by reasoning about the potential decisions made by other players. In the logistics market, each party is comprised of selfish actors aiming at optimizing their own goals – they make decisions by reasoning about the potential reactions of other interacting actors and predict the potential responses from these actors. FFs compete for the limited resources and capacity from carriers with the best price. Carriers also compete for business from FFs. On the one hand, each actor is free to act independently. A shipper can choose any FF. A FF proposes charges to shippers by making its own pricing decision and then assigning cargo received to available carriers. Carriers design their freight tariff schemes to achieve their own goals.

This research is inspired by a game theoretic view of supply chain management (SCM), which examines the interactions between different players to find the equilibrium decision for each decision maker (Groznik & Heese, 2010; Leng & Parlar, 2005; J. Li & Wang, 2010; J. C. Lu et al., 2012; Ni & Li, 2012; Wu, 2012). A brief review of game theoretic applications in supply chain management can be found in Leng and Parlar (2005). In this type of research, game theory is applied to find the equilibrium decision of each player when a stable set of circumstances is reached. In this equilibrium state, each player has no incentive to unilaterally change and deviate from its current decision. As a result, each player has found its optimal decision by considering the reactions of the others.

However, current research focuses more on the interaction between two tiers of actors/actions, for instance, between two manufacturers and one retailer (Wu, 2012); two horizontally competitive suppliers and their vertical common retailer (J. C. Lu et al., 2012); an upstream supplier and a downstream firm (Ni & Li, 2012); a single manufacturer and two competing retailers (Groznik & Heese, 2010); or competing suppliers and one assembler (J. Li & Wang, 2010). In this research, FFs are intermediaries who connect upstream shippers and downstream carriers; thus we have to investigate a three-tier interaction between shippers, FFs and carriers. The multi-level interaction adds new complexity to the problem formulation using game theory.

In addition, most of the previous research assumes demand to be a function of either market size, price and level of service (J. C. Lu et al., 2012; Wu, 2012); price related parameters (J. Li & Wang, 2010); or the utility and preference of various parties (Groznik & Heese, 2010; Ni & Li, 2012). Typically, a demand function is given to describe how these factors will influence the demand of a particular player. However, in this research, demand from shippers may or may not be elastic due to factors internal to shippers and external market conditions. Rather than defining a demand function for FFs, we only take into account how the decisions made by FFs will affect those made by shippers. The price and level of service by FFs are the only factors deciding a shipper's preference (utility) in selecting a FF. The capacity in the logistics market is taken to be inelastic in the short term due to the long lead time required to build vessels, the bulky nature of the supply, and the high costs of taking a ship temporarily out of service. The emphasis of this research is on how FFs can use available information to make pricing decisions when demand and supply are fixed

Game theory has been applied to examine non-pricing issues related to FFs. Saeed (2012) compared vertical and horizontal cooperation among FFs using game theory by defining the total demand for a particular FF through its customers' utility (preference) when the FF is selected. This utility is assumed to be a function of the charge and level of service (waiting time of customers and frequency of trucks) of the FF. Krajewska and Kopfer (2006) proposed models for collaboration among independent FFs through a preprocessing phase followed by coalition profit optimization and profit sharing phases. Xiao and Yang (2007) examined the interaction between shippers, carriers and infrastructure companies. In Xiao and Yang (2007)'s work, they focus on the equilibrium flows of the system rather than the decision making problems of a specific tier by considering the potential behaviors and reactions of other tiers.

Game theoretic concepts such as sub-game perfect Nash equilibrium (J. C. Lu et al., 2012; Xiao & Yang, 2007) and backward induction (J. Li & Wang, 2010; Ni & Li, 2012; Xiao & Yang, 2007) have been applied in supply chain management and FF decision making. However, the interaction between all the three parties together in the logistics chain has not yet been considered.

2.4 Reinforcement Learning (RL)

The objective in reinforcement learning is to improve the performance of an entity by building an update policy for various decisions made by the entity. This is mainly performed by trial and error without the model of the environment, but resulting actions are used to improve the process. Each action results in a feedback that may be a reward or a punishment. These data are then applied to update the learning models into the future.

Reinforcement learning mechanisms can be categorized into two types: non-associative and associative learning mechanisms. For the non-associative reinforcement learning, the actions to be taken by a given player are not associated with its current state and vice-versa for the associative learning. Action-value and softmax methods for non-associative learning, and state-action-reward-state-action (SARSA) and Q-Learning methods for associative learning are considered in this research. According to Sutton and Barto (1998), both the SARSA and the Q-Learning methods are also called Temporal-Difference (TD) learning methods because the learning is based on a difference between the estimates of the value of functions at two different times. The advantage of TD-learning methods is to make it possible to learn directly from the raw data without a model of the environment.

With Reinforcement learning, FFs are able to learn from their performance in previous interactions, and then use this knowledge to improve their future decisions. According to Ertel (2011), at a specific time n, and repeatedly over the total time period N, the world can be described by a state $s_n \in \mathcal{S}$, where the set $\mathcal{S}$ is an abstraction of the actual possible states of the world. When a particular agent takes an action $a_n \in \mathcal{A}$ at time n, the state of the world changes and results in the state s_{n+1} at time $n+1$. A state transition function is used to determine the new state $s_{n+1} = \delta(s_n, a_n)$. This function is defined by the environment but cannot be influenced by any actor. After executing an action a_n at time n, the agent obtains an immediate reward $r_n = r(s_n, a_n)$, which is always dependent on the current state and the action taken. During learning, $r_n > 0$ and $r_n < 0$ result in positive and negative reinforcements respectively, and $r_n = 0$ means that the agent receives no immediate feedback for the action a_n. A decision $\pi: \mathcal{S} \rightarrow \mathcal{A}$ is a mapping from states to actions, which helps the agent learn an optimal decision based on its experiences. This is also the goal in RL - a decision is optimal if it maximizes reward in the long run. In order to measure the performance of a decision π, a discounted reward is defined to quantify the performance of the decision starting at state s_n:

$$V^{\pi}(s_n) = r_n + \gamma r_{n+1} + \gamma^2 r_{n+2} + \cdots = \sum_{i=0}^{\infty} \gamma^i r_{n+i} \tag{2.1}$$

An alternative average reward function can be used:

$$V^{\pi}(s_n) = \lim_{h\to\infty} \sum_{i=0}^{h} r_{n+i} \tag{2.2}$$

A decision π is optimal if all states s satisfy the following condition:

$$V^* = V^{\pi^*}(s) \geq V^{\pi}(s) \tag{2.3}$$

Based on the concept of dynamic programing (Hillier, 2010), given the current state, an optimal decision for the remaining stages is independent of the decisions adopted in previous stages. The optimal immediate decision depends only on the current state and not on how you got there. As a result, the future decisions for the remaining stages will constitute an optimal decision regardless of the decision made in previous stages (Taha, 2007). Using the discounted reward, we have:

$$\begin{aligned} V^*(s_n) &= \max_{a_n, a_{n+1}, a_{n+2}, \dots} (r_n + \gamma r_{n+1} + \gamma^2 r_{n+2} + \cdots) \\ &= \max_{a_n} \left[r_n + \gamma \max_{a_{n+1}, a_{n+2}, \dots} (r_{n+1} + \gamma r_{n+2} + \cdots) \right] \\ &= \max_{a_n} [r_n + \gamma V^*(s_{n+1})] \end{aligned} \tag{2.4}$$

Then, the optimal decision can be obtained:

$$\pi^*(s_n) = \underset{a_n}{argmax}\left[r_n + \gamma V^*\big(\delta(s_n, a_n)\big)\right] \quad (2.5)$$

In previous research, reinforcement learning has been used to examine freight and passenger transportation related issues: for example, the design of train marshaling plans considering the group layout of freight cars (Hiroshima, 2012); the transfer distance of locomotives (Hirashima, 2011); the generation of plans for vehicle routing (Mostafa & Talaat, 2010); and the examination of uncertainty, bounded rationality, and strategic choice behavior of travelers (Han & Timmermans, 2006). However, there has not been work on incorporating reinforcement learning in FF's pricing decision making.

2.5 Multi-Agent System (MAS)

Multi-agent systems are systems composed of multiple interacting computing agents (Wooldridge, 2002). An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators (Russel & Norvig, 2010). This paradigm has been used to represent organizations, functions, resources, and even human beings. MASs are considered suitable for the simulation of any phenomenon, scientific or behavioral, in order to understand the underlying dynamics of complex systems effectively (Govindu & Chinnam, 2007). It is considered to be one of the powerful technologies for the development of large-scale distributed systems to deal with the uncertainty in a dynamic environment (Chen & Cheng, 2010). This technology is motivated by the desire to get deeper insight into the system that is not captured by traditional modeling approaches (Borshchev, 2013).

According to Russel and Norvig (2010), an agent is able to interact with its environment through sensors and actuators (shown in Fig. 2.2). In general, an agent's choice of action at any given instant can depend on the entire percept sequence observed to date. The percept refers to the agent's perceptual inputs at any given instant, and the percept sequence refers to the complete history of everything the agent has ever perceived. As a result, the behavior of an agent can be described by the action that is performed after any given sequence of percepts. The agent function represents an agent's external characterization and internal rules or principles that guide the agent's decision-making. It maps any given percept sequence to an action. An agent function is implemented by an agent program which describes what percepts an agent will take as input and what actions will be returned. These percepts may include current information, information learnt via past experience as well as the anticipation of the future. Agents are categorized into four main types: simple reflex agent, model-based reflex agents, goal-based agents, and learning agents. Details of each type of these agents are presented in Table 2.1.

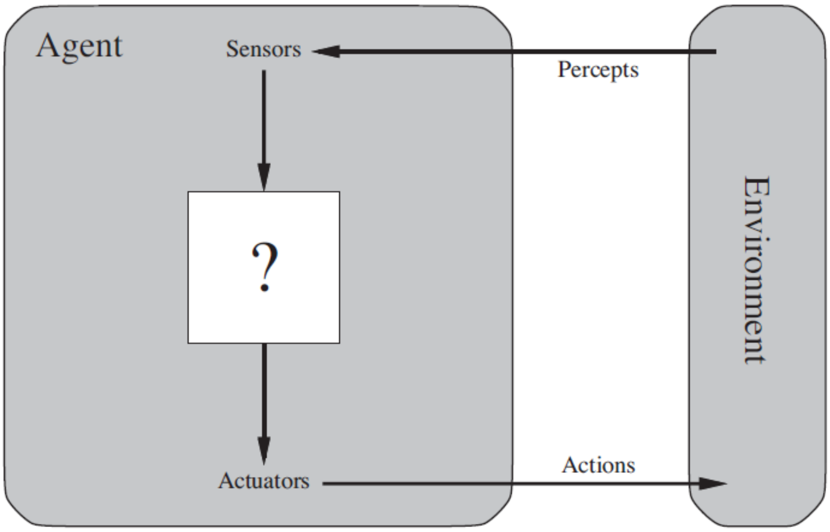

Fig. 2.2 Agent and its interaction with the environment (Russel & Norvig, 2010)

Table 2.1 Different types of agents (Russel & Norvig, 2010)

Agent type	Descriptions
Simple reflex agents	They select actions on the basis of the current percept in a condition-action manner, ignoring the rest of the percept history.
Model-based reflex agents	They maintain some sort of internal state and keep this state updated as time goes by. They also have some sort of knowledge regarding how the world evolves independently of the agent and how the agent's own action influences the world in a given internal stage. After examining all the above aspects, they make decisions based on condition-action rules.
Goal-based agents	They maintain a current state description (similar to model-based reflect agent) together with a sort of goal information that describes situations that are desirable.
Utility-based agents	Compared with goal-based agent, utility-based agents provide a more general performance measure by utility rather than just provide a binary distinction between "happy" and "unhappy".
Learning agents	They are capable of learning from past actions to improve the performance of future decisions.

This research is also inspired by the multi-agent approach applied in supply chain management, in which MAS technology is used to facilitate the modeling and simulation of a supply chain and its dynamics (Fox et al., 2000; J. Li & Chan, 2013; Swaminathan et al., 1998). A review related to multi-agent systems application in supply chain management can be found in Lee and Kim (2008). Zhang et al. (2006) considered integrating manufacturers' production activities with suppliers, customers and partners within wide and open supply chain networks to help manufacturers remain competitive in complex global political and economic scenarios. Pan and Choi (2013) used a multi-agent approach to consider the negotiation on price and delivery date between manufacturer and supplier in fashion supply chain. W. Y. Liang and Huang (2006) used agent-based technology to forecast demand in a multi-echelon supply chain.

MAS technology has also been used to examine non-pricing issues related to FFs. Chan et al. (2012) proposed a multi-agent-based framework to enhance the automation of cargo consolidation and equalization in the air industry, and to facilitate cargo processing and generation of flight plans. Air cargo received by a FF can be processed more efficiently and flight plans can be generated automatically for FFs. Shum and Ng (2010) proposed an agent-based framework to streamline cargo handling for air freight forwarding industry. However, there has not been any work done to model the interaction between FFs and other parties using a MAS approach; neither has there been work on using the MAS framework to support the pricing decision by FFs.

2.6 Gaps and Future Research Needed

First of all, there has not been much work addressing the issue of pricing decisions by FFs in a situation involving shippers, FFs, and carriers. Operations research and mathematical programming are the most commonly used problem solving approaches. Problems are typically described from a single perspective or from the perspective of the whole system (system optimality and centralized decision making). The potential reactions of other entities are considered as constraints or simply omitted. However, in reality shippers, FFs, and carriers can pursue their own goals (user equilibrium and decentralized decision making). They can consider tradeoffs but do not need to sacrifice benefits for the achievement of system optimality. Conflict or congruence between the goals of different participants brings about competition or cooperation, and the decisions made by the different parties will change accordingly. However, it is difficult to say which goal, user equilibrium or system optimality, is better: system optimality improves the gains from the perspective of the whole system, whilst sub-system optimality, or user equilibrium, is more realistic in the real world implementation. In the real world most rational entities aim at maximizing their own goals, and will only consider achieving system optimality when their payoffs can be improved. Under the system optimality condition, the sum of all individuals' gains is maximized and the sum of individuals' payoffs under the system optimality condition will be no worse than that in sub-system optimality condition, which brings the incentives for different entities to cooperate and coordinate to achieve system optimality. In addition, these decisions should also be sensitive to the market, as well as to the decisions made by other participants. Game theory appears to be the best means of considering all the above issues when examining the pricing decisions of FFs. A game theoretic approach for a FF's pricing decision is presented in Chapter 3 .

In addition, most of the literature presented in Section 2.1focuses on optimizing the decision of FFs only with respect to current information, and learning from previous transactions has not been incorporated. However, in a highly competitive market, FFs can improve their pricing performance by adapting their decisions vis-à-vis their competitors. These decisions should be sensitive to the changes in the market as well as the decisions made by other actors. In this research, reinforcement learning is proposed to assist FFs in their pricing decisions. How learning approaches can be incorporated in a FF's pricing decision is proposed in Chapter 4 and Chapter 5 .

Further more, in operations research models, even though it is claimed that optimal decisions (for FFs) can be derived via these models, these optimal solutions do not take account of iterated decision making among FFs, shippers and carriers. In the real world, goals and objectives are likely to change depending on information received as a result of interaction between the parties and through negotiation. The nature of the interaction also depends on the decisions made by the different parties. In other words, the negotiation between FFs and shippers or carriers can play a significant part in the decisions of all participants but this interaction has rarely been taken into consideration in previous research. The current "optimal" decision may not be optimal across the whole planning horizon, because the environment and the behavior of different participants may change and evolve over time. Multi-agent system (MAS) is a suitable technique to evaluate the various pricing decisions approaches that can be adopted by FFs. In a multi-agent simulation, each participant is represented by a software agent, which functions as an autonomous entity able to sense the environment and react accordingly. Through MAS, it is possible to examine the effect various decision making approaches adopted by FF. Multi-agent systems are built and multi-agent simulations are conducted in Chapter 4 and Chapter 5 .

CHAPTER 3 PRICING DECISIONS WITH COMPLETE INFORMATION

3.1 Introduction

This chapter presents a game theoretic (GT) approach to assist FFs with their pricing decisions. The aim of this chapter is to investigate how a given FF can formulate its optimal pricing decision in face of competition when it has complete information of the entire system. The potential reactions from other parties (shippers and carriers) and the competition from other FFs are taken into account by applying game theory. The information that is available to the FF is shown in Fig. 3.1. About the internal information, the FF knows its own objective as well as its preference when selecting preferred carriers. About the external information on shippers, the FF knows: 1) number of shippers; 2) each shipper's demand of cargo movement; 3) each shipper's selection behavior for the preferred FF; and 4) each shipper's objective. About the external information on competing FFs', the FF knows: 1) number of competing FFs; 2) each competing FF's objectives; and 3) selection behavior of preferred carriers. About the external information on carriers, the FF knows: 1) number of carriers; 2) each carrier's selection behavior of preferred FFs; 3) full freight rate scheme; and 4) capacity.

In this chapter, the real world interaction between shippers, FFs, and carriers (discussed in Section 1.2) is represented as an extensive form game. A Multinomial Logit (MNL) model is used to represent the selection behavior of shippers. The concepts of Nash equilibrium in an extensive form game and backward induction are used to solve the equilibrium pricing decision under different scenarios. The results of the study give an insight into: 1) how a FF's equilibrium prices are determined in face of competition under various scenarios; 2) how a FF could achieve optimal pricing performance in face of competition; and 3) how various key factors (demand, shipper's price sensitivity etc.) affect a FF's pricing performance in the game. Several practical suggestions for FFs in pricing decisions are proposed.

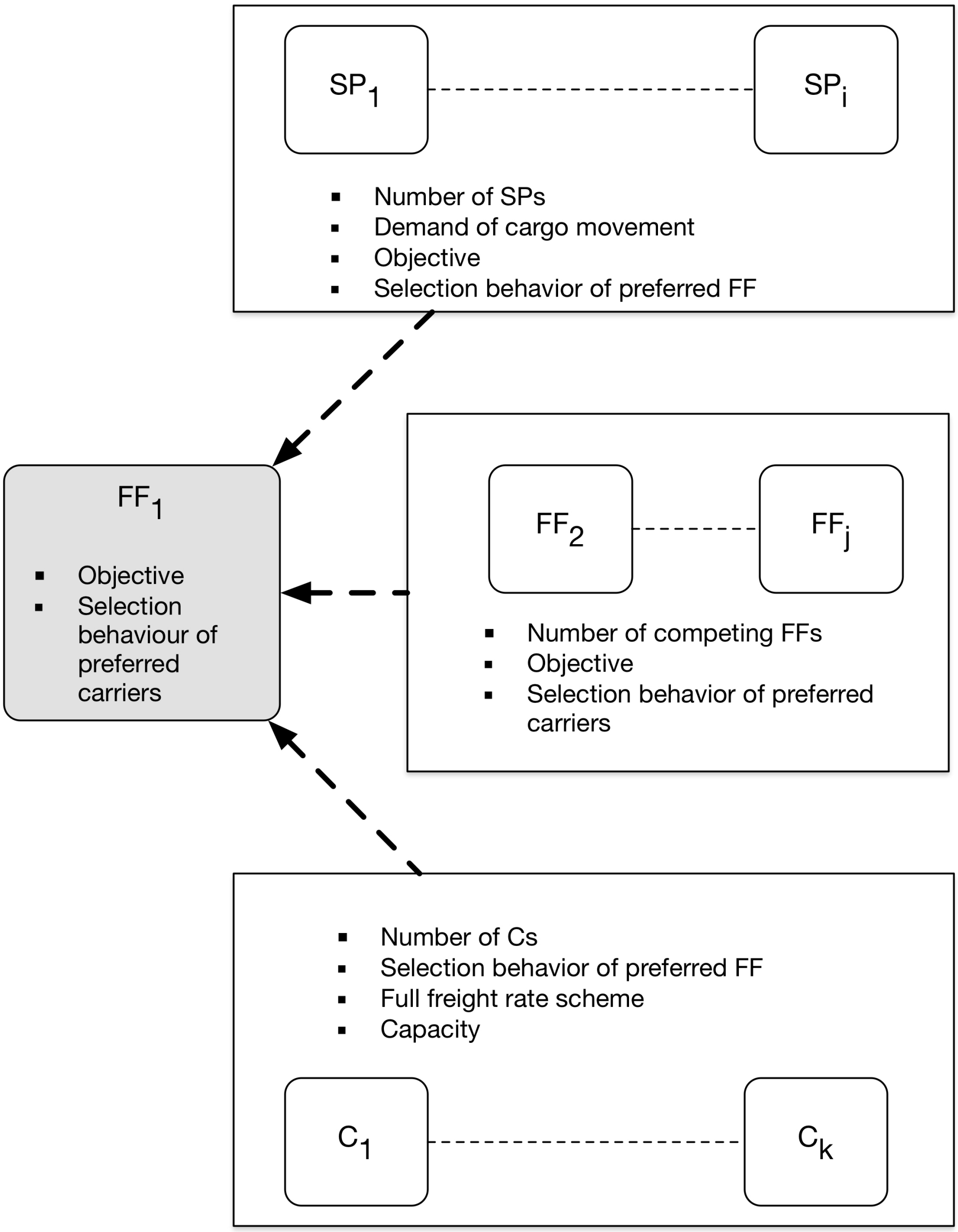

Fig. 3.1 A FF is able to access full information of the entire system

3.2 Representing the Interaction between SPs, FFs and Cs as a Game

This research proposes to model the three-party interaction between shippers (SP_k), FFs (FF_i), and carriers (C_j) as an extensive form game. The focus is on the pricing decision by FFs. Fig. 3.2 describes the game from the perspective of a particular SP_k. The total analysis horizon is divided into N analysis time periods, and within each analysis period n this game has the following moves:

- Move 1: SP_k decides either to use a FF (LH_1) or design its own cargo movement plan (RH_1). All shippers make their decision simultaneously based on the information made available to them – FFs' proposed charges (or carriers' tariff scheme), schedule and level of service.
    - LH_1: SP_k selects one FF, and this FF receives all the cargo from SP_k (outsourcing shipper).
    - RH_1 : SP_k implements its own cargo movement plan (self-fulfillment shipper, SF_k).
- Move 2: Self-fulfillment shippers (RH_2) and FFs (LH_2) assign cargo among available carriers simultaneously.
- Move 3: carriers move cargo to the destination and adjust their tariffs (RH_3, LH_3). The game advances to the next analysis period ($n + 1$) and starts again from move 1.

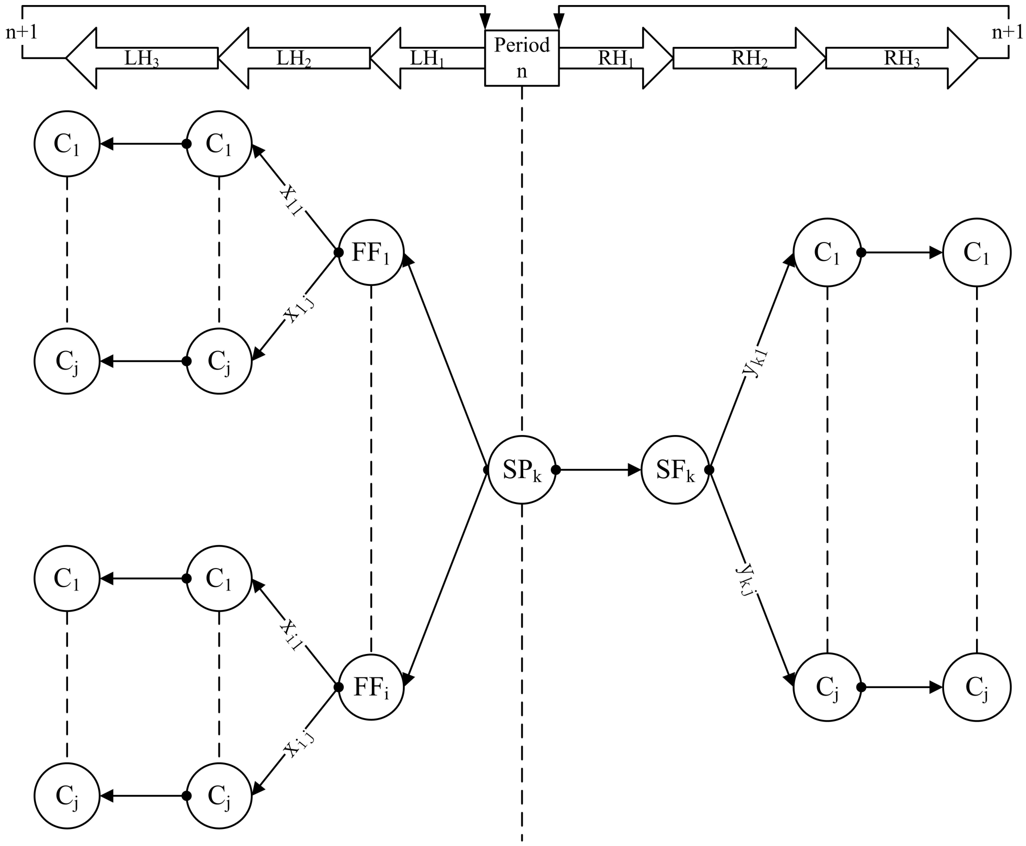

Fig. 3.2 Extensive form game between shipper, FF and carrier.

3.3 Non-Cooperative Game between SPs, FFs and Cs

3.3.1 Game Description and Assumptions

As shown in Fig. 3.3, an example involving two shippers ($SP_k, k = 1{,}2$), two FFs ($FF_I, i = 1{,}2$) and two carriers ($C_j, j = 1{,}2$) is used to illustrate how a given FF can make pricing decisions using the proposed GT approach.

It is assumed that SP_k needs to transport V_k unit of cargo from an origin A to a destination B. Both shippers want to transport cargo between the same origin and destination pair. There are two carriers serving the above OD pair, and they are available to both FFs. C_j has an available capacity of CA_j, and its charging scheme is denoted as $R_j(x)$ - the unit cargo movement charge with respect to a given cargo volume x.

The demand comes from shippers, which is supposed to be satisfied by supply offered by carriers. On the supply side, the market is assumed to be oversupplied: the total supply offered by carriers is greater than the demand for cargo movement – both carriers have more than enough capacity to meet the demand from both shippers. In order to take into account competition between FFs for the most cost-effective carrier, it is assumed that each carrier has the capacity to serve the demand of any shipper, but neither carrier can service the combined demand from both shippers.

We also assume that the supply from carriers may fluctuate but not rapidly in the short term. Carriers may adjust their fleet size in response to demand but that is not the focus of this research. We adopt the above assumptions because the emphasis of the research is on the design of pricing decisions by FFs in a competitive oversupplied market. The problem is to formulate a pricing decision by taking into account the potential reactions of other actors, given the demand from shippers and the supply from carriers. A FF assures its own profitability if it can beat its competitors' prices. However, pricing by FFs will influence a shipper's selection of a preferred service provider.

The vertical interaction between shippers and FFs as well as that between FFs and carriers are incorporated in this game. Under the assumption of non-cooperative behavior, each player is assumed to be a selfish entity trying to maximize its own goals.

The first stage of the vertical interaction happens between shippers and FFs. The goal of the shippers is to minimize their total cargo movement cost. They are both outsourcing shippers, and independently choose one FF based on charges proposed by the FFs. They have no incentive to split the cargo between FFs because outsourcing by shippers is common in the real world operations. Most of the shippers do not want to design and execute their own cargo movement plans. Instead, they prefer to partner third party logistics companies and rid themselves of non-core services and additional functions that are not typical for a company. The FFs are assumed to be NVOCCs, and their goal is to maximize individual total profit. No FF has the incentive to cooperate with the other; instead, they compete for limited cargo from shippers and available capacity from carriers. Communication and information exchange are not possible between the FFs, and they do not form a coalition.

The second stage of the vertical interaction happens between FFs and carriers. FFs' objective is to minimize cost by splitting cargo among available carriers by making the best combination of carriers. In the end, carriers transport cargo physically from origin to destination. Carriers' objectives are represented by their charging schemes. But how carriers adjust their pricing scheme is not the focus of this research.

Horizontal competitions within tiers are also incorporated in this game.

FFs compete for business from shippers by proposing prices, and compete for the most cost-effective carrier by splitting cargo between carriers. The competition between carriers is represented by carriers' charging scheme. It is assumed that carriers always prefer FFs offering larger volume of cargo. The compotation between shippers is not considered for current research.

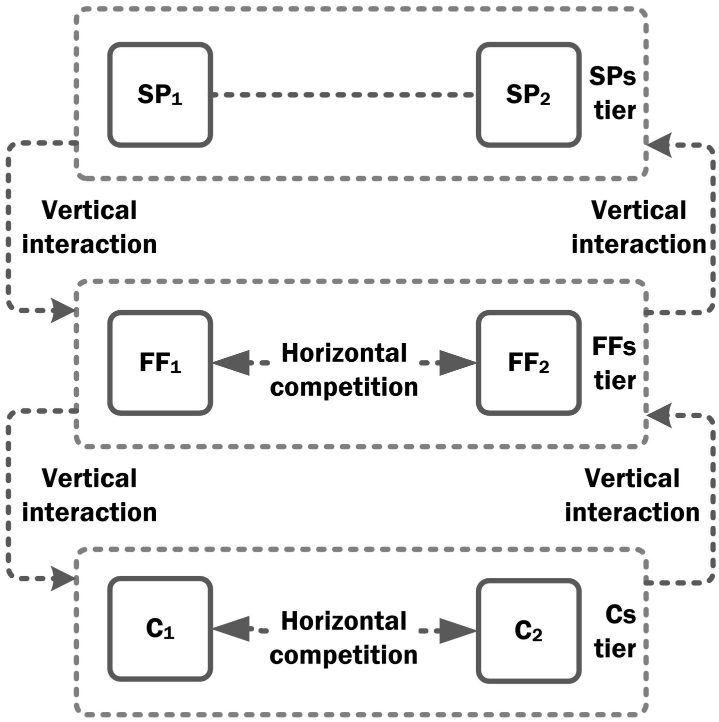

Fig. 3.3 Research context for GT approach

3.3.2 Game-Theoretic Approach for FF Pricing Decision

In the six-player game, going from move 1 to move 2 can be treated as an extensive-form game, in which each player knows the sequence of its moves. In order to obtain the equilibrium decision for each player, the game is divided into two sub-games - a sub-game is a small portion of a game starting at a specific node of the entire game (Geckil & Anderson, 2010). In this example, two sub-games are identified: a) sub-game 1 - interaction between shipper and FF; b) sub-game 2- interaction between FF and carrier. The decision of each player is in a sub-game perfect Nash equilibrium (SPNE) in an extensive form game when these decisions constitute a Nash equilibrium in each of the sub-games (Hargreaves-Heap & Varoufakis, 2004). A specific player will make its own utility-maximizing decision, given the decision of ‘‘upper level’’ players and the information of ‘‘lower level’’ players (Xiao & Yang, 2007). “Upper level” players are the ones who have finished their moves, and ‘‘Lower level’’ players are the ones who will move afterwards by referring to the move of this player. In order to find the Nash equilibrium of this game, the concept of backward induction (Hargreaves-Heap & Varoufakis, 2004) is applied, where a player moving first will consider what the player moving next would do. Players work out their best decisions by reasoning backwards and inducing their beliefs about what constitutes the wisest choice by starting at the end and then moving to the beginning. By using backward induction, the analysis begins from the end of the game to its beginning, i.e. first sub-game 2 and then sub-game 1 is considered.

In sub-game 2, the problem for FFs is how to assign cargo received from shippers among carriers. Here, it is assumed that shippers’ decision about the choice of FF is already known, and FFs need only to consider how to devise a combination of carriers to minimize costs for the volume of cargo received.

In sub-game 1, each shipper chooses a particular FF according to price sensitivity and allocates all the cargo to it. FFs need to set the price of their services by maximizing their own profits. From sub-game 2, FFs receive information on the payment to carriers. With this information, FFs are able to determine their own charges to quote to shippers so as to generate profits in this sub-game.

3.3.2.1 Sub-game 2: Interaction between FFs and Cs

Sub-game 2 represents the interaction between FFs and carriers. If TV_i units of cargo are received from shippers in sub-game 1, FF_i proceeds to split the cargo between the carriers in this sub-game. Although there is an oversupply of capacity in the market, it is assumed that a single carrier cannot handle all the cargo from both shippers simultaneously. As a result, both FFs compete for capacity from the more cost-effective carrier, and the decision of one FF will affect that of the other. If both FFs propose to give their cargo to the same carrier simultaneously, one or both of them will lose economy of scale because of the need to split part of the cargo to the other carrier. As a result, both FFs are willing to contract with the carrier with the lower freight rate to avoid splitting cargo so as to enjoy the economy of scale and the quantity discount.

The aim of both FFs is to reduce the total costs that may occur. A given carrier's remaining capacity to FF_i equals to its total capacity less the space that has already been given to the other $FF_{\underline{i}}$ (the competitor to FF_i is denoted as $FF_{\underline{i}}$). As a result, the cargo splitting plan of FF_i $(i = 1,2)$ can be expressed as the following optimization model:

$$Min\ \pi F_i = \sum_j R_j(x_{ij})x_{ij} \tag{3.1}$$

Subject to:

$$\sum_j x_{ij} = TV_i \tag{3.2}$$

$$\sum_j x_{\underline{i}j} = TV_{\underline{i}} \tag{3.3}$$

$$0 \le x_{ij} \le CA_j - x_{\underline{i}j}\ , \qquad j = 1,2 \tag{3.4}$$

Where, πF_i is the total cargo movement cost to FF_i; x_{ij} is the volume of cargo FF_i intends to offer to C_j; $x_{\underline{i}j}$ is the volume that C_j has already accepted from the other $FF_{\underline{i}}$; and $R_j(x)$ is C_j's unit cargo charge with respect to cargo volume x. The objective of FF_i is to minimize total payment (cost) to carriers (Equation (3.1)). Constraint (3.2) ensures that all the cargo received by FF_i is transported. Constraint (3.3) ensures that the potential reaction of the other $FF_{\underline{i}}$ is taken into consideration. Constraint (3.4) ensures that the volume of cargo FF_i intends to give a carrier is within its current available capacity. In the formulation, FF_i takes into account the potential move of the other $FF_{\underline{i}}$ by involving the other FF's decision variable $x_{\underline{i}j}$ in its decision making problem (constraint(3.3)), because the moves of FF_i and $FF_{\underline{i}}$ are represented by x_{ij} and $x_{\underline{i}j}$ respectively. However the value of $x_{\underline{i}j}$ is treated as known in the decision making problem of FF_i.

FF_i's optimal response (x_{ij}^*) when $FF_{\underline{i}}$'s reaction ($x_{\underline{i}j}$) is given can be expressed as:

$$x_{ij}^* \in arcMin\, \pi F_i\left(x_{ij}^* \middle| x_{\underline{i}\,j}\right) \tag{3.5}$$

It is obvious that x_{ij}^* is a function $f_i(\cdot)$ of $x_{\underline{i}\,j}$, and thus the best reaction of FF_i when the reaction of the other $FF_{\underline{i}}$ is known would be (the two carriers are notated as C_j and $C_{\underline{j}}$ respectively):

$$\begin{cases} x_{ij}^* = f_i(x_{i\underline{j}}) \\ x_{i\underline{j}}^* = TV_i - x_{ij}^* \end{cases} \tag{3.6}$$

Based on equation (3.6), the Nash equilibrium solution for both FFs is obtained by solving the following set of equations:

$$\begin{cases} x_{ij}^* = f_i(x_{\underline{i}j}) \\ x_{i\underline{j}}^* = TV_i - x_{ij}^* \\ x_{\underline{i}j}^* = f_{\underline{i}}(x_{ij}) \\ x_{\underline{i}\underline{j}}^* = TV_{\underline{i}} - x_{\underline{i}j}^* \end{cases} \tag{3.7}$$

It is assumed that both carriers are using linear pricing schemes with quantity discount (equation (3.8)), in which a_j represents the carrier's marginal cost, and b_j is a parameter affecting the profit distribution between carriers (Xiao & Yang, 2007):

$$R_j(x) = a_j - b_j x\,, \qquad j = 1,2 \tag{3.8}$$

Upon substituting equation (3.8) into equation (3.1), the cost function of FF_i becomes:

$$\pi F_i = \sum_j \left(a_j - b_j x_{ij}\right) x_{ij} \tag{3.9}$$

It is assumed that both carriers prefer the FF with the larger cargo volume, and will serve that FF first before allocating the remaining capacity to the other FF. Without loss of generality, it is assumed that $TV_1 > TV_2$ (when $TV_1 = TV_2$, both carriers become indifferent to the choice between FFs). Then, this sub-game can be solved as a Stackelberg game: FF_1 moves first to assign cargo between the carriers, followed by FF_2 assigning cargo by using the remaining capacity.

With $i = 1$, minimizing (3.9) with respect to constraints (3.2) to (3.4) results in the optimal move for FF_1:

$$x_{11}^* = \begin{cases} 0, & if\ \dfrac{TV_1}{2} \leq d_1 \\ TV_1, & if\ \dfrac{TV_1}{2} > d_1 \end{cases} \tag{3.10}$$

Where:

$$d_i = \frac{a_1 - a_2 + 2b_2 TV_i}{2b_1 + 2b_2} \tag{3.11}$$

Following this, FF_2 assigns its cargo by making use of the remaining capacity of both carriers. With $i = 2$ and x_{11}^*, minimizing (3.9) with respect to constraints (3.2) to (3.4) results in the optimal response of FF_2:

$$x_{21}^* = \begin{cases} \dfrac{TV_2 - C_2 + x_{12}^* - |TV_2 - C_2 + x_{12}^*|}{2}, & if\ M \le d_2 \\ \dfrac{TV_2 + C_1 - x_{11}^* - |TV_2 - C_1 + x_{11}^*|}{2}, & if\ M > d_2 \end{cases} \tag{3.12}$$

Where:

$$M = \frac{2TV_2 + C_1 - C_2 + x_{12}^* - x_{11}^*}{4} - \frac{|TV_2 - C_2 + x_{12}^*| + |C_1 - TV_2 - x_{11}^*|}{4} \tag{3.13}$$

(x_{11}^*, x_{21}^*) is a Nash equilibrium because both FFs' decisions are the best responses given the reactions of the other. This is the best outcome either can achieve by competing against each other. Both have no incentive to deviate from this equilibrium unilaterally because deviating will not make either of them better off.

3.3.2.2 Sub-game 1: Interaction between SPs and FFs

In this sub-game, each shipper needs to choose one FF based on its own price-preference. According to discrete choice theory (Ben-Akiva & Lerman, 1985), a decision maker's choice from a set of mutually exclusive and collectively exhaustive alternatives can be modeled on the assumption of utility maximization. The alternative with the highest utility among the available alternatives should be selected. The utility function of a decision maker is formulated in terms of observable independent variables and unknown parameters. Because it is impossible to specify and estimate a discrete choice model that will always succeed in predicting the choice of an individual, the concept of randomness is invoked. The true utility of the alternatives is considered a random variable, and the probability that an alternative is chosen is defined as the probability that it has the greatest utility among the alternatives. Therefore, when SP_k faces the choice between two alternative FFs, its utility when selecting FF_i can be defined as:

$$U_{ki} = v_{ki} + \varepsilon_{ki} \tag{3.14}$$

Where v_{ki} is the systematic (representative or deterministic) component of U_{ki}, and ε_{ki} is the random part (disturbances or random components). In this research, the deterministic part of SP_k's utility when choosing FF_i is defined as:

$$v_{ki} = \alpha_k - \beta_k PD_i \tag{3.15}$$

Where PD_i is the pricing decision of FF_i, and α_k and β_k are positive constants associated with SP_k's preference when selecting a FF. β_k reflects the SP_k's sensitivity towards price, and is associated with a negative sign because increasing price makes the choice of that FF less preferred. Based on the multinomial logit (MNL) model, the probability for SP_k to choose FF_i can be quantified as:

$$p_{ki} = \tau\left(PD_i, PD_{\underline{i}}\right) = \frac{e^{v_{ki}}}{e^{v_{ki}} + e^{v_{k\underline{i}}}} \tag{3.16}$$

Where p_{ki} is a function of both PD_i and $PD_{\underline{i}}$. Each FF then needs to set the price of its services so as to maximize its own profit. Sub-game perfection assumes that at each stage of the game, players' actions are the best replies to one another when players know the precise "node" they are at (Hargreaves-Heap & Varoufakis, 2004). However, in this example, both FFs do not know this "node" because the amount of cargo they receive depends on their pricing decision PD_i, which affects shippers' preference towards a FF. Furthermore, the price per unit cargo paid to carriers depends on the total amount of cargo the FF receives. If the proposed charges are too high, a FF may risk not getting any cargo from shippers. However, if the proposed charges are too low, the revenue obtained may not be sufficient to cover payment to the carriers even though the FF receives more cargo. In order to solve this sub-game, the concept of sequential equilibrium is used. Sequential equilibrium is aimed at composing decisions which are the best replies to another player's actions in stages of a game where players are uncertain regarding their precise location (or node) in the game. For a given FF, four possible scenarios can be identified with respect to its location in sub-game 1. Although each FF cannot tell which scenario will occur, the probability of each scenario can be estimated. x_{ij}^{l} is defined as the amount of cargo FF_i offers to C_j in scenario l, where $l = 1,2,3,4$. Table 3.1 shows the four possible scenarios, where P_l is the probability for scenario l to occur; cv_{li} is the amount of cargo FF_i obtains in scenario l; and z_{li} is FF_i's average unit cost in scenario l.

Table 3.1 Possible scenarios

Scenario l	Probability P_l	Cargo volume – cv_{li}		Average unit cost – z_{li}	
		FF_1	FF_2	FF_1	FF_2
1	$P_1 = p_{11}p_{21}$	$cv_{11} = \mathrm{V}_1 + \mathrm{V}_2$	$cv_{12} = 0$	z_{11}	$NA.$
2	$P_2 = p_{12}p_{22}$	$cv_{21} = 0$	$cv_{22} = \mathrm{V}_1 + \mathrm{V}_2$	$NA.$	z_{22}
3	$P_3 = p_{11}p_{22}$	$cv_{31} = V_1$	$cv_{32} = V_2$	z_{31}	z_{32}
4	$P_4 = p_{12}p_{21}$	$cv_{41} = V_2$	$cv_{42} = V_1$	z_{41}	z_{42}

The average unit cost (z_{li}) for FF_i in scenario l can be estimated as:

$$z_{li} = \frac{\sum_j R_j(x_{ij}^z)x_{ij}^z}{\sum_j x_{ij}^z} \tag{3.17}$$

Because SP_k will chose one FF and has no incentive to split cargo among different FFs, p_{ki} $(k = 1,2)$ will always satisfy the following equations:

$$p_{ki} + p_{k\underline{i}} = 1 \tag{3.18}$$

Using Table 3.1, the expected total profit of FF_i $(i = 1,2)$ can be calculated as:

$$E(TP_i) = \sum_l P_l cv_{li} (PD_i - z_{li}) \tag{3.19}$$

Based on Equation (3.19) and Table 3.1, the expected profit of FF_i $(i = 1,2)$ can be calculated as:

$$\begin{aligned} E(TP_1) = {} & p_{11}p_{21}(V_1 + V_2)(PD_1 - z_{11}) + p_{11}p_{22}V_1(PD_1 - z_{31}) \\ & + p_{12}p_{21}V_2(PD_1 - z_{41}) \end{aligned} \tag{3.20}$$

$$E(TP_2) = p_{11}p_{22}(V_1 + V_2)(PD_2 - z_{22}) + p_{11}p_{22}V_2(PD_2 - z_{32}) + p_{12}p_{21}V_1(PD_2 - z_{42}) \tag{3.21}$$

The first order derivative of the expected total profit of FF_i $(i = 1,2)$ is:

$$\frac{\partial E(TP_1)}{\partial PD_1} = (PD_1V_1 - V_1z_{31} - p_{21}V_1z_{11} - p_{21}V_2z_{11} + p_{21}V_1z_{31} + p_{21}V_2z_{41})\frac{\partial p_{11}}{\partial PD_1} + (PD_1V_2 - V_2z_{41} - p_{11}V_1z_{11} - p_{11}V_2z_{11} + p_{11}V_1z_{31} + p_{11}V_2z_{41})\frac{\partial p_{21}}{\partial PD_1} + p_{11}V_1 + p_{21}V_2 \tag{3.22}$$

$$\frac{\partial E(TP_2)}{\partial PD_2} = (-PD_2V_1 - V_2z_{32} + p_{22}V_2z_{22} + p_{22}V_1z_{22} + p_{21}V_2z_{32} + p_{21}V_1z_{42})\frac{\partial p_{11}}{\partial PD_2} + (-PD_2V_2 - V_1z_{42} + p_{12}V_1z_{22} + p_{12}V_2z_{22} + p_{11}V_2z_{32} + p_{11}V_1z_{42})\frac{\partial p_{21}}{\partial PD_2} + p_{12}V_1 + p_{22}V_2 \tag{3.23}$$

According to Equation (3.16), we obtain:

$$p_{ki}e^{U_{k\underline{i}}} = e^{U_{ki}}(1 - p_{ki}) \tag{3.24}$$

Taking the logarithm of both sides of Equation (3.24) yields:

$$ln(p_{ki}) + U_{k\underline{i}} = U_{ki} + ln\,(1 - p_{ki}) \tag{3.25}$$

Taking first order derivative of both sides of Equation (3.25) with respect to PD_1 results in:

$$\frac{1}{p_{k1}}\frac{\partial p_{k1}}{\partial PD_1} - \frac{1}{1 - p_{k1}}\frac{\partial(1 - p_{k1})}{\partial PD_1} = \frac{1}{p_{k1}}\frac{\partial p_{k1}}{\partial PD_1} + \frac{1}{1 - p_{k1}}\frac{\partial(p_{k1})}{\partial PD_1} \tag{3.26}$$
$$= -\beta_k$$

Then we will obtain:

$$\frac{\partial(p_{k1})}{\partial PD_1} = -\beta_k p_{k1}(1 - p_{k1}) = D_k \tag{3.27}$$

Similarly, we can obtain:

$$\frac{\partial(p_{k1})}{\partial PD_2} = \beta_k p_{k1}(1 - p_{k1}) = -D_k \tag{3.28}$$

Solving Equation (3.29) with respect to Equation (3.27) and Equation (3.22) results in the optimal pricing decision PD_1^* for FF_1 given the reaction of

FF_2 (shown in Equation (3.30)). Similarly, Solving Equation (3.29) with respect to Equation (3.28) and Equation (3.23)results in the optimal pricing decision PD_2^* for FF_2 given the reaction of FF_1 (shown in Equation (3.33)). Then we calculate the first order derivative of total profit for FF_i $(i = 1,2)$, and set it equal to zero:

$$\frac{\partial E(TP_i)}{\partial PD_i} = 0 \tag{3.29}$$

The optimal pricing decision for FF_1 given the reaction of FF_2 can be calculated as:

$$PD_1^*|_{PD_2} = \frac{D_1[V_1 z_{31} + p_{21} Q_1] + D_2[V_2 z_{41} + p_{11} Q_1] - p_{11} V_1 - p_{21} V_2}{D_1 V_1 + D_2 V_2} \tag{3.30}$$

Where:

$$Q_1 = (V_1 + V_2) z_{11} - V_1 z_{31} - V_2 z_{41} \tag{3.31}$$

$$D_k = -\beta_k p_{k1}(1 - p_{k1}) \tag{3.32}$$

Similarly, we obtain the optimal pricing decision for FF_2 given the reaction of FF_1:

$$PD_2^*|_{PD_1} = \frac{D_1[V_1 z_{42} + p_{22} Q_2] + D_2[V_2 z_{32} + p_{12} Q_2] - p_{12} V_1 - p_{22} V_2}{D_1 V_1 + D_2 V_2} \tag{3.33}$$

Where:

$$Q_2 = (V_1 + V_2) z_{22} - V_2 z_{32} - V_1 z_{42} \tag{3.34}$$

Equations (3.30) and (3.33) are the optimal pricing decision of FF_i when the decision of $FF_{\underline{i}}$ is known. These equations represent the response rules regarding how a given FF could react to the pricing decisions made by the other FF. We note that PD_i^* is a function of $(p_{ki}, p_{\underline{k}i}, p_{k\underline{i}}, p_{\underline{ki}})$, and p_{ki} is a function of $(PD_i, PD_{\underline{i}}, \beta_k, \beta_{\underline{k}})$ – indicating how the decisions of the other FF and shippers are involved; however, neither PD_1^* nor PD_2^* can be given in closed form. The equilibrium pricing decisions for both FFs can be obtained by solving the system of equations constituting of (3.30) and (3.33):

$$\begin{cases} PD_1^*|_{PD_2} = \dfrac{D_1[V_1 z_{31} + p_{21}Q_1] + D_2[V_2 z_{41} + p_{11}Q_1] - p_{11}V_1 - p_{21}V_2}{D_1V_1 + D_2V_2} \\ PD_2^*|_{PD_1} = \dfrac{D_1[V_1 z_{42} + p_{22}Q_2] + D_2[V_2 z_{32} + p_{12}Q_2] - p_{12}V_1 - p_{22}V_2}{D_1V_1 + D_2V_2} \end{cases} \tag{3.35}$$

For optimality, the second order derivative of $E(TP_i)$ at PD_i^* should satisfy:

$$\left.\frac{\partial^2 E(TP_i)}{\partial (PD_i)^2}\right|_{PD_i = PD_i^*} < 0 \tag{3.36}$$

The second order derivative of $E(TP_i)$ at PD_i^* (shown in Equation (3.36)) can be expressed as:

$$\begin{aligned} \frac{\partial^2 E(TP_1)}{\partial (PD_1)^2} &= (2V_1 - D_2Q_1)D_1 + (2V_2 - D_1Q_1)D_2 \\ &+ (PD_1V_1 - V_1z_{31} - p_{21}Q_1)\frac{\partial^2 p_{11}}{\partial (PD_1)^2} \\ &+ (PD_1V_2 - V_2z_{41} - p_{11}Q_1)\frac{\partial^2 p_{21}}{\partial (PD_1)^2} \end{aligned} \tag{3.37}$$

$$\frac{\partial^2 E(TP_2)}{\partial(PD_2)^2} = (2V_1 - D_2Q_2)D_1 + (2V_2 - D_1Q_2)D_2$$
$$+ \{-PD_2V_1 + V_1z_{42} + (1 - p_{21})Q_2\}\frac{\partial^2 p_{11}}{\partial(PD_1)^2} \tag{3.38}$$
$$+ \{-PD_2V_2 + V_2z_{32} + (1 - p_{11})Q_2\}\frac{\partial^2 p_{21}}{\partial(PD_2)^2}$$

Taking the second order derivative on both sides of Equation (3.25) with respect to PD_1 and PD_2 results in:

$$\frac{\partial^2 p_{k1}}{\partial(PD_1)^2} = \frac{\partial D_k}{\partial PD_1} = 2\beta_k D_k p_{k1} - \beta_k D_k \tag{3.39}$$

$$\frac{\partial^2 p_{k1}}{\partial(PD_2)^2} = 2\beta_k D_k p_{k1} - \beta_k D_k \tag{3.40}$$

Substituting Equation (3.39) into Equation (3.37), and Equation (3.40) into Equation (3.38) respectively results in:

$$\left.\frac{\partial^2 E(TP_1)}{\partial(PD_1)^2}\right|_{PD_1=PD_1{}^*}$$
$$= D_1[2V_1 + (\beta_1 - 2\beta_1 p_{11})(-PD_1V_1 + V_1z_{31} + Q_1p_{21} - Q_1D_2)] \tag{3.41}$$
$$+ D_2[2V_2 - Q_1D_1 + (\beta_2 - 2\beta_2 p_{21})(-PD_1V_2 + V_2z_{41} + Q_1p_{11})]$$

$$
\begin{aligned}
&\left.\frac{\partial^2 E(TP_2)}{\partial (PD_2)^2}\right|_{PD_2=PD_2^*} \\
&\qquad = D_1[2V_1 + (\beta_1 - 2\beta_1 p_{11})(-PD_2V_1 + V_1 z_{42} + Q_2 p_{22} - Q_2 D_2)] \\
&\qquad + D_2[2V_2 - Q_2 D_1 + (\beta_2 - 2\beta_2 p_{21})(-PD_2 V_2 + V_2 z_{32} + Q_2 p_{12})]
\end{aligned}
\tag{3.42}
$$

3.4 Numerical Experiment

In this section, the problem formulations of the preceding sections are used to solve numerical experiments. The results of these numerical simulations are useful in drawing insights into FF's pricing decisions under competition. The effect of shippers' price sensitivity and level of demand can also be studied. This has useful implications for FFs.

Assume that two shippers want to move containers from city A to city B. Each shipper is going to outsource their vehicle movement tasks to a FF. There are two FFs in the market, and they are available to both shippers. Two vessels (carriers) serve the route from city A to city B, and both FFs are going to make use of these two carriers to design their cargo transportation plans. Other than mentioned above, all the other features of the three-tier interaction remain unchanged as shown in Fig. 3.3. The two shippers (SP_1 & SP_2) need to transport $V_1 = 250$ TEUs and $V_2 = 200$ TEUs respectively, and the two carriers (C_1 & C_2) can both provide slots for $ca_1 = ca_2 = 300$ TEUs. The charging scheme (all-in price) of both carriers is shown in Fig. 3.4.

Table 3.2 The charging scheme of carriers

C_j	a_j	b_j	ca_j	Description
C_1	$a_1 = 650$	$b_1 = 0.6$	$ca_1 = 300$	Prefer the FF who offers larger volume of cargo
C_2	$a_2 = 600$	$b_2 = 0.3$	$ca_2 = 300$	

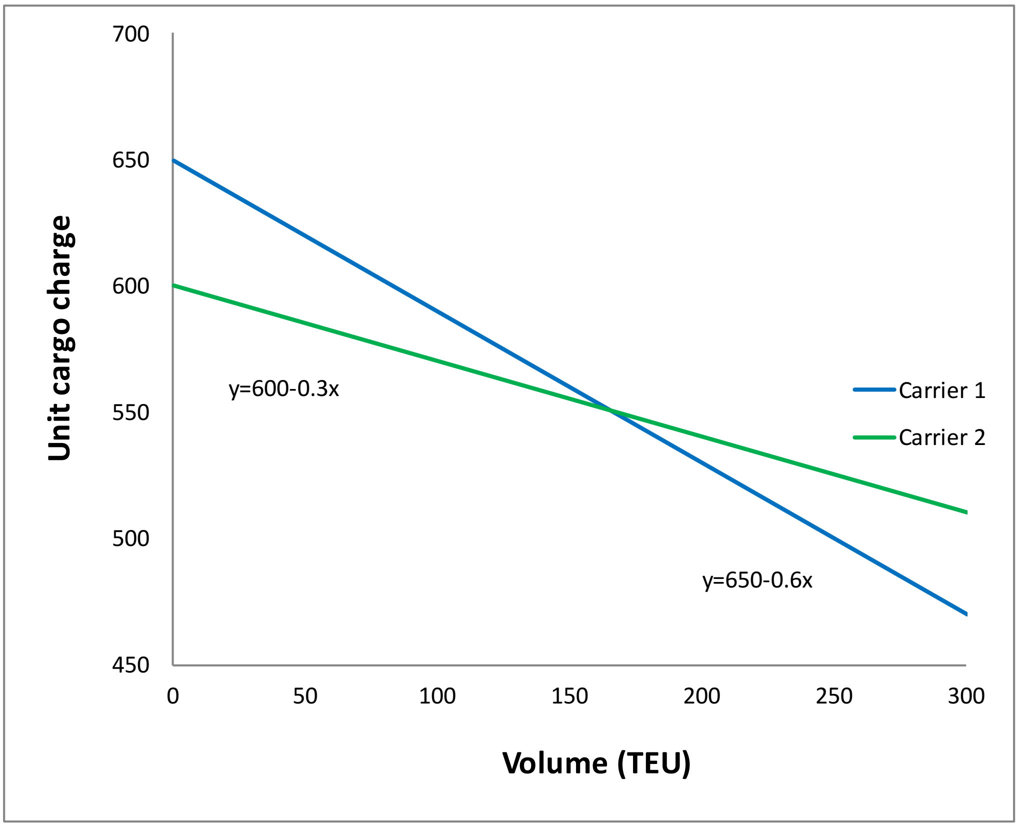

Fig. 3.4 The charging scheme of both carriers

As discussed in Section 3.3.2.2, a shipper's preference for a particular

FF is determined by its utility function (Equations (3.14) and (3.15)). Equation (3.16) can be further simplified to:

$$p_{ki} = \tau\left(PD_i, PD_{\underline{i}}\right) = \frac{e^{v_{ki}}}{e^{v_{ki}} + e^{v_{k\underline{i}}}} = \frac{1}{1 + e^{v_{k\underline{i}} - v_{ki}}} = \frac{1}{1 + e^{\beta_k\left[PD_i - PD_{\underline{i}}\right]}} \quad (3.43)$$

From Equation (3.43), we see that the probability p_{ki} for a given FF_i to be selected by SP_k is determined by FF_i's price advantage $\left(PD_i - PD_{\underline{i}}\right)$ over its competitor $FF_{\underline{i}}$, as well as the shipper's price sensitivity β_k. Price sensitivity measures how the price quoted by a FF affects the utility of a given shipper: a larger β_k makes a shipper more sensitive to price differences between two competing FFs. α_k represents a given shipper's intrinsic level of satisfaction when the price equals to zero. As it does not appear in Equation (3.43), it can be set to any arbitrary value.

Section 3.4.1 presents solutions to the equilibrium pricing decision by FFs. Shippers are modeled as having either a high or low level of price sensitivity (P-S), and we name them as "high P-S shipper" or "low P-S shipper" respectively. The examples are examined with respect to three combinations of shippers: 1) both high P-S shippers; 2) a combination of a high P-S shipper and a low P-S shipper; 3) both low P-S shippers.

The effect of price sensitivity β_k on FFs' equilibrium pricing decisions is discussed in Section 3.4.2. How the level of demand of shippers will affect

FFs' equilibrium pricing decisions is discussed in Section 3.4.3.

3.4.1 Solution of Equilibrium Pricing Decision Model

The aim of this section is to examine the equilibrium pricing decision by FFs when shippers have different level of price sensitivity. Shippers' and carriers' parameters are listed in Table 3.3.

Table 3.3 Model parameters for Shipper and carrier

Expt.	Shipper				
	SP_k	P-S	β_k	α_k	V_k
1	SP_1	H	0.050	$\alpha_1 = 0.9$	$V_1 = 250$
	SP_2	H	0.060	$\alpha_2 = 0.8$	$V_2 = 200$
2	SP_1	H	0.050		
	SP_2	L	0.006		
3	SP_1	L	0.005		
	SP_2	L	0.006		

3.4.1.1 Subgame 2 – Interaction between FFs and Cs

In subgame 2, FFs need to split the cargo among the carriers by referring to the pricing scheme of carriers (Table 3.3). To do so, each FF needs to estimate the potential cost associated with the different scenarios listed in Table 3.1. As discussed in Section 3.3.2.1, the optimal cargo split can be obtained by solving the optimization problem given by Equations (3.1) to (3.4). Its solution yields the potential costs that occur under different scenarios, as shown in Table 3.4.

Table 3.4 Potential costs for different scenarios in subgame 2

Scenario l	Cargo volume FF_1	Cargo volume FF_2	Average unit cost FF_1	Average unit cost FF_2
1	$V_1 + V_2 = 450$	0	$Z_{11} = 498.33$	NA.
2	0	$V_1 + V_2 = 450$	NA.	$Z_{22} = 498.33$
3	$V_1 = 250$	$V_2 = 200$	$Z_{31} = 500.00$	$Z_{32} = 540.00$
4	$V_2 = 200$	$V_1 = 250$	$Z_{41} = 540.00$	$Z_{42} = 500.00$

3.4.1.2 Sub-game 1 - Interaction between FFs and SPs

After solving sub-game-2, FFs need to formulate their proposed charges to shippers. In sub-game-1, a shipper's price sensitivity will directly influence the price a FF proposes. The pricing decision of both FFs are derived by Equations (3.30) and (3.33). We cannot obtain a closed-form solution for the equilibrium price by solving (3.35). However, we could use a non-linear programing algorithm to find a solution. The equilibrium prices obtained under the combinations of shippers are solved using the optimization toolbox in Matlab which uses a dogleg trust-region algorithm for solving a system of nonlinear equations (Matlab, 2015); the results are shown in Table 3.5. In the equilibrium condition, both FFs propose the same price, obtain the same unit cargo cost, unit cargo profit, and get the same expected volume. Table 3.5 also suggests that the higher the price sensitivity of the shipper, the lower will be the equilibrium price and expected unit profit even though the expected unit cost and total cargo volume remain the same.

Table 3.5 Equilibrium price for $FF_1 \& FF_2$

Expt..	P-S combination of shippers	Equilibrium Price	Unit cargo cost	Total cargo volume	Unit cargo profit
1	High, High	536.35			28.46
2	High, Low	551.01	508.05	225.00	43.12
3	Low, Low	866.96			359.07

3.4.2 Effect of Price Sensitivity on Equilibrium Price

The aim of this section to investigate the effect of shippers' price sensitivity on the equilibrium price by FFs. An experiment was conducted in which the price sensitivity of the shipper, β_k was varied between [0.005, 0.05]. β_k was varied within the above range because we would like to see how the variation of price sensitivity will affected the equilibrium price and pricing performance of different FFs. Both shippers are assumed to have the same price sensitivity.

The equilibrium price – price sensitivity curve plotted in Fig.4.1 shows that there is an inverse relationship between equilibrium price and price sensitivity. In addition, this relationship is non-linear. Fig.4.1 also shows that there are three distinct parts of the curve. Furthermore, both FFs achieve the same level of unit cost (SGD 508.05) and cargo volume (225 TEUs) at the equilibrium, and the total demand is split equally between FFs.

The practical significance of the above findings is that FFs should be sensitive to the price sensitivity of their clients. This brings an incentive for FFs to price segment their clients. Price segmentation, also known as price discrimination in economics, is charging different customers different prices for an otherwise identical or similar product (Nagle et al., 2011). Lower prices prevent high price sensitive shippers from switching service providers, but a desired profit margin should still be maintained by FFs. It is vice versa when FFs interact with high price sensitive shippers - good value-added services and level of service should be provided. Through consultation with industry practitioners, we also found that the key clients, shippers with large and regular demand for cargo movement, seldom switch logistics service providers. They try to avoid switching costs and the need to get used to a new business partner. They examine price, level of service, and previous experiences to decide whether to sign a long term contract or not. On the other hand, small or individual clients, shippers with low and infrequent demand for cargo movement, switch logistics service providers quite often because they believe these service providers offer a similar level of service. They are more sensitive to the price they are going to pay, and are willing to switch to a new service provider as long as a better price can be obtained.

However, it is not possible to determine the value of this willingness-to-pay – β_k except from past transactions or on a trial and error basis. By evaluating their previous transactions, FFs can quantify each shipper's price sensitivity. Surveys can also be conducted but the results would have to be treated with a fair amount of scepticism because other shippers may not be willing to reveal confidential information – e.g. the basis of choosing preferred FFs.

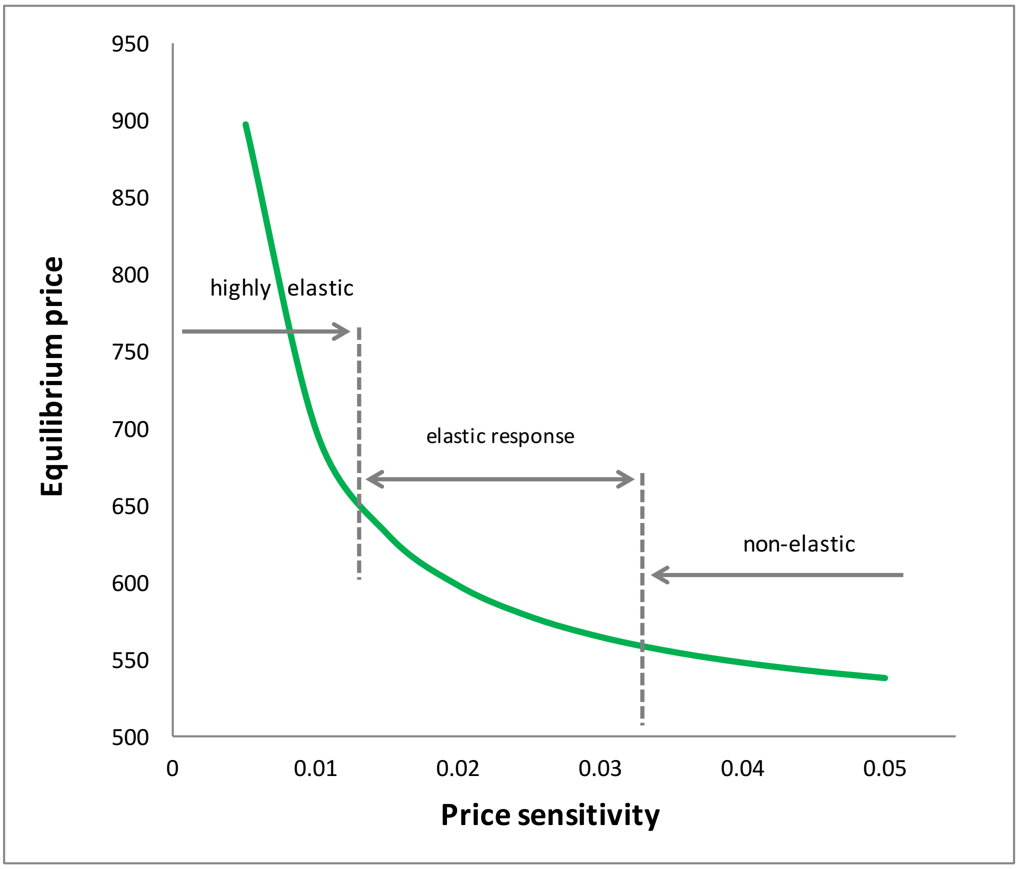

Fig. 3.5 Effect of price sensitivity on equilibrium price

3.4.3 Effect of Demand on Equilibrium Price

The aim of this section is to investigate how the level of demand from shippers affects the equilibrium price by FFs and other performance indicators. The total demand was varied from 0 TEU to 600 TEUs, and the demand was split equally between both shippers. The demand is assumed to vary within the above range because the total capacity offered by carriers is 600TEUs in the market and the market is assumed to be oversupplied. As the purpose of conducting the experiment is to examine how the variation of demand will affect equilibrium price and other performance indicators, both shippers' value of price sensitivity (set to 0.03). The parameters for the carriers remain unchanged as shown in Table 3.3.

Fig. 3.6 plots equilibrium price (per unit cargo) and unit cargo cost against total demand. The figure shows that both the price curve and the cost curve consist of three segments and the transitions happen at two critical cargo volumes - 167 TEUs and 300 TEUs. When the volume is 167 TEUs, FFs' preference for the preferred carrier shifts from C_2 to C_1. This corresponds to the breakeven point between the carriers' charging schemes shown in Fig. 3.7. When the demand goes beyond 300 TEUs, this is beyond the capacity of either carrier.

Both the price curve and the cost curve decrease as the volume of demand increases from 0 to 300 TEUs. This is because both carriers offer volume discounts and FFs enjoy higher discounts as they offer more cargo to the carriers. Starting at a volume of 167 TEUs, the price curve and the cost curve drops more dramatically because of the differences in the carriers' charging scheme – C_1 uses a low price for a large amount of cargo although the price for a small amount of cargo is relatively higher (vice versa for the C_2). This difference between carriers causes the difference in the slope of the cost curve and the price curve. When the volume of demand goes beyond 300 TEUs, the two curves rise in the beginning to reach a maximum before decreasing thereafter. This is because once the total demand exceeds the capacity of the most cost-effective carrier, FFs have to split their cargo and use the other less cost-effective carrier. The cost curve then goes down because the unit cost is calculated as the expected cost with respect to four possible scenarios shown in Table 3.1. The cost goes up in scenarios 1 and 2 but falls in scenarios 3 and 4. The probability-weighted effect on costs in these four scenarios drives the expected cost down as total demand increases. The slops of the cost curve in turn affect the price curve. However, the peaks of the two curves are not at the same volume of demand.

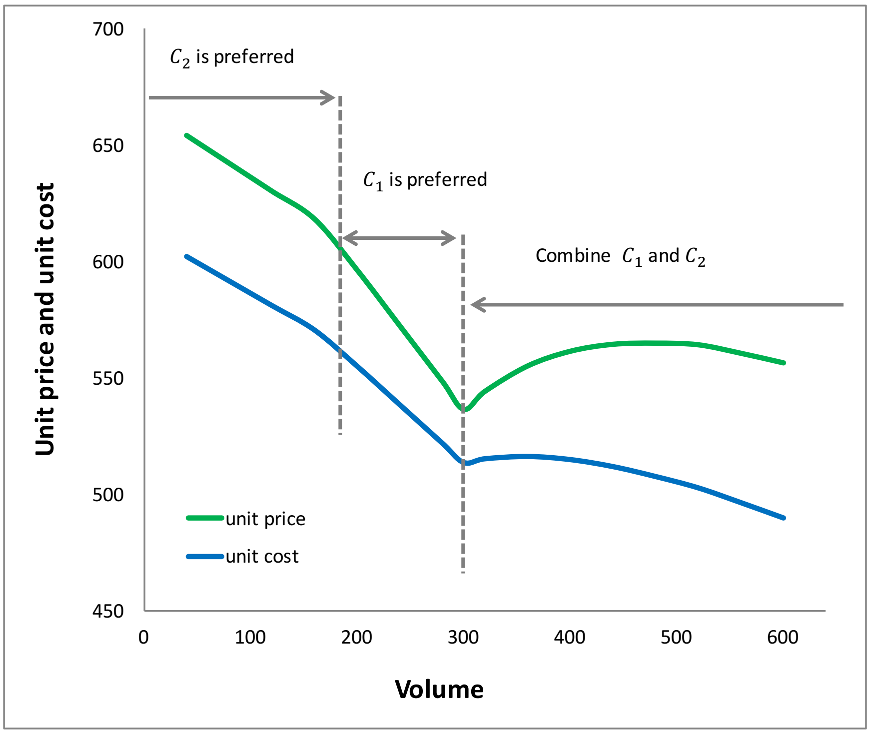

Fig. 3.6 Equilibrium unit price vs. unit cost

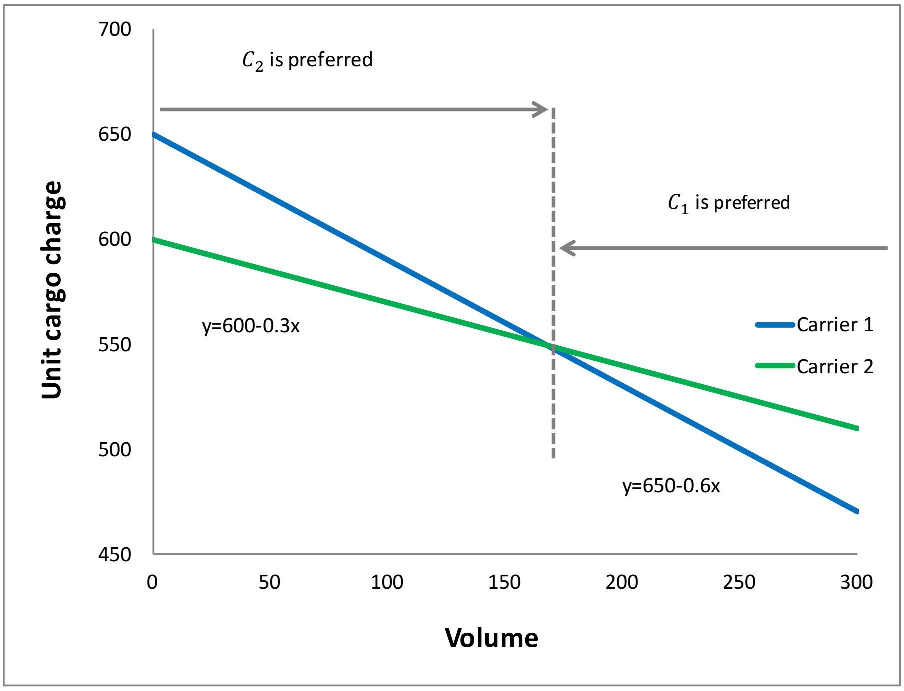

Fig. 3.7 Carrier's charging scheme

Fig. 3.8 plots equilibrium unit cargo profit against demand, whilst Fig. 3.9 plots equilibrium markup against demand. They show that in order to maximize the expected total profit, FFs do not apply the same markup as the demand changes. The markup and the profit are determined by the objective of maximizing the total expected profit. FFs apply higher markups when the volume is very low or very high and decrease their markup as the demand become closer to the capacity of the individual carriers – 300 TEUs.

The implication to the FFs is that the markup should not be identical for all market conditions and demand levels. They should determine the optimal markup with respect to their current demand level and expected cost.

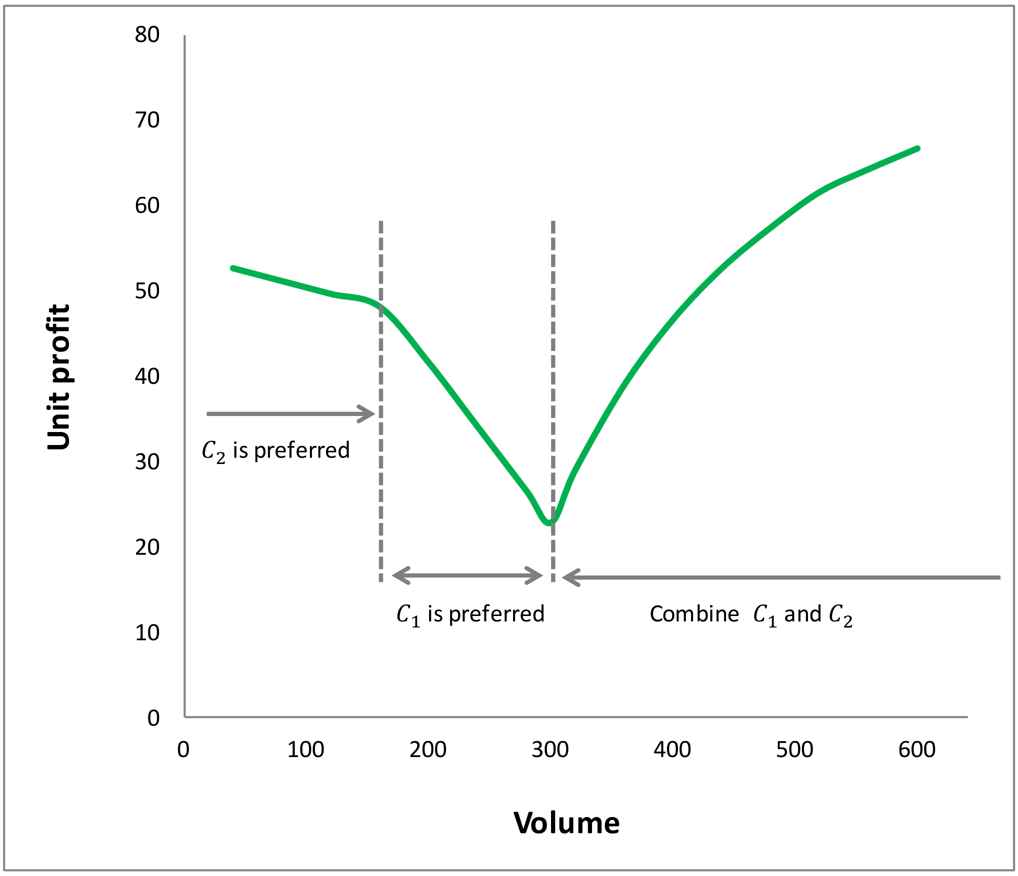

Fig. 3.8 Equilibrium unit cargo profit

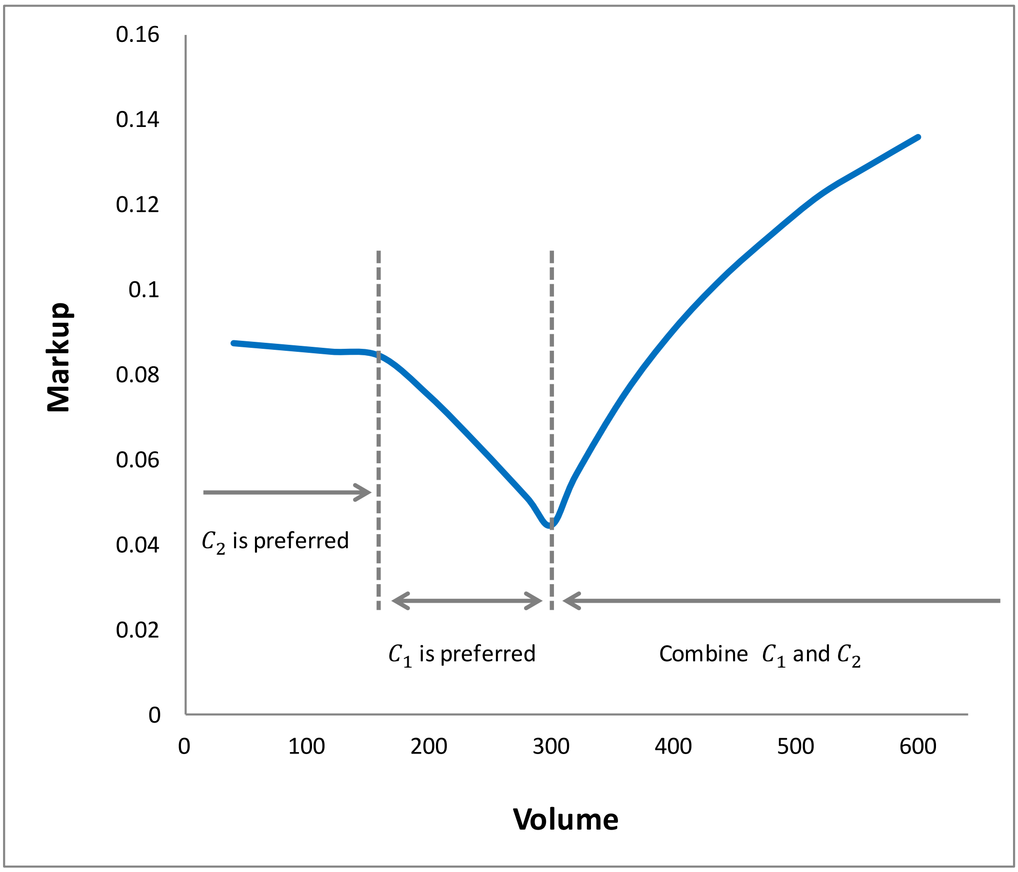

Fig. 3.9 Equilibrium markup

Fig. 3.10 plots total revenue and total cost against demand, whilst Fig. 3.11 plots total profit against demand. Total revenue and total cost keep increasing as demand increases; however, total profit first increases till demand reaches 200 TEUs and then drops a bit until demand reaches 300 TEUs. Beyond that, total profit keeps growing. This is because the objective of FFs is to maximize the expected profit given current demand level and carriers' charging schemes. The growth or loss of total profit is the outcome of balancing price, cost and cargo volume so as to maximize total profit. Total profit increases with demand as the growth of marginal revenue is greater than that of marginal cost, and vice versa when total profit drops. Specifically, in this experiment, as demand increases from 0 TEU to 200 TEUs, FFs can attract more cargo by lowering the markup - the marginal profit gained by volume growth is greater than that lost due to price drop. Similarly, total profit drops as demand increases from 200 TEUs to 300 TEUs because of the outcome of balancing price, cost and volume so as to maximize profit. Despite a total profit drop, the price is still the optimal decision for FFs as deviating from this price leads to more severe decrease in total profit. When demand is beyond 300 TEUs, total profit increases again because higher markup is used to cover the potential cost boost due to the usage of both carriers and the competition for limited capacity from the preferred carrier. FFs may have to split cargo among carriers (lose economy of scale) or use the less cost-effective one (failure in competition).

The implication to FFs is that an improvement of pricing performance can be achieved by balancing price, cost and volume of cargo for the purpose of maximizing total profit. An increase in price improves per unit cargo profit but hurts cargo volume growth. In addition, pricing decisions should be profit-driven rather than cost-driven. However, most logistics companies and literature related to FF operation issues focus more on cost reduction only because they believe the market rates are already established and the only thing they could do is to reduce cost. The shortcomings of cost-driven pricing are obvious - it is impossible to determine a product’s unit cost before determining its volume. It fails to account for the effect of price on volume of business secured and volume on cost, which directly leads to pricing decisions that undermine profits (Nagle et al., 2011). The results may be overpricing in weak markets and underpricing in strong ones - exactly opposite to a prudent decision. As a result, a FF quoting price should ask whether the change in price will result in a change in revenue that is more than sufficient to offset a change in total fixed and variable costs.

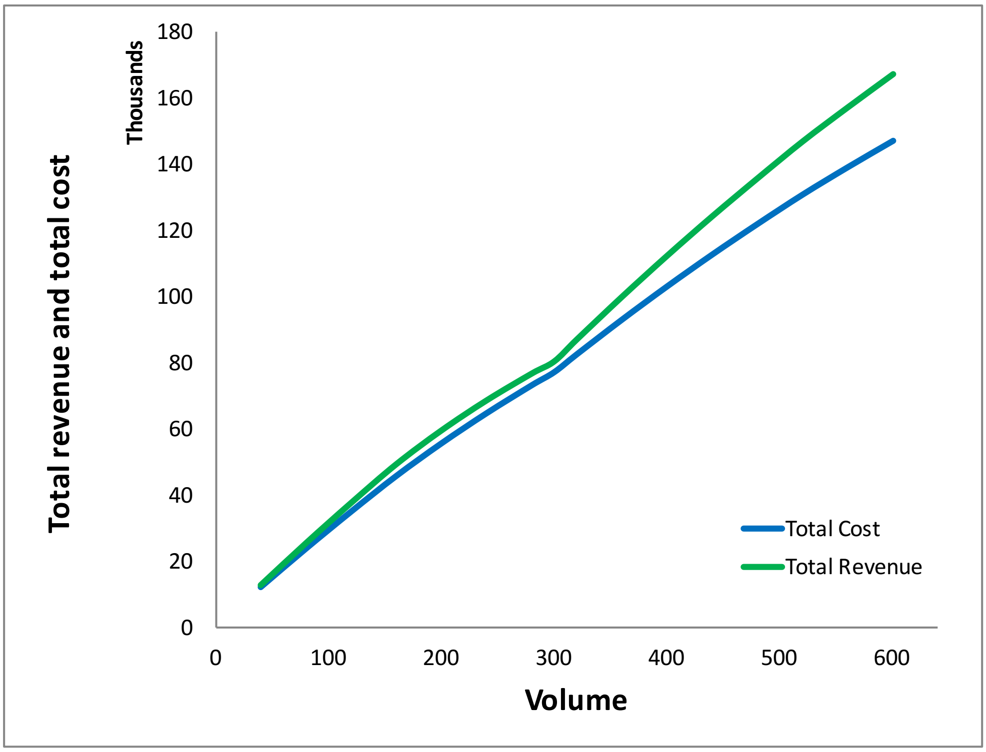

Fig. 3.10 Total revenue and total cost at equilibrium

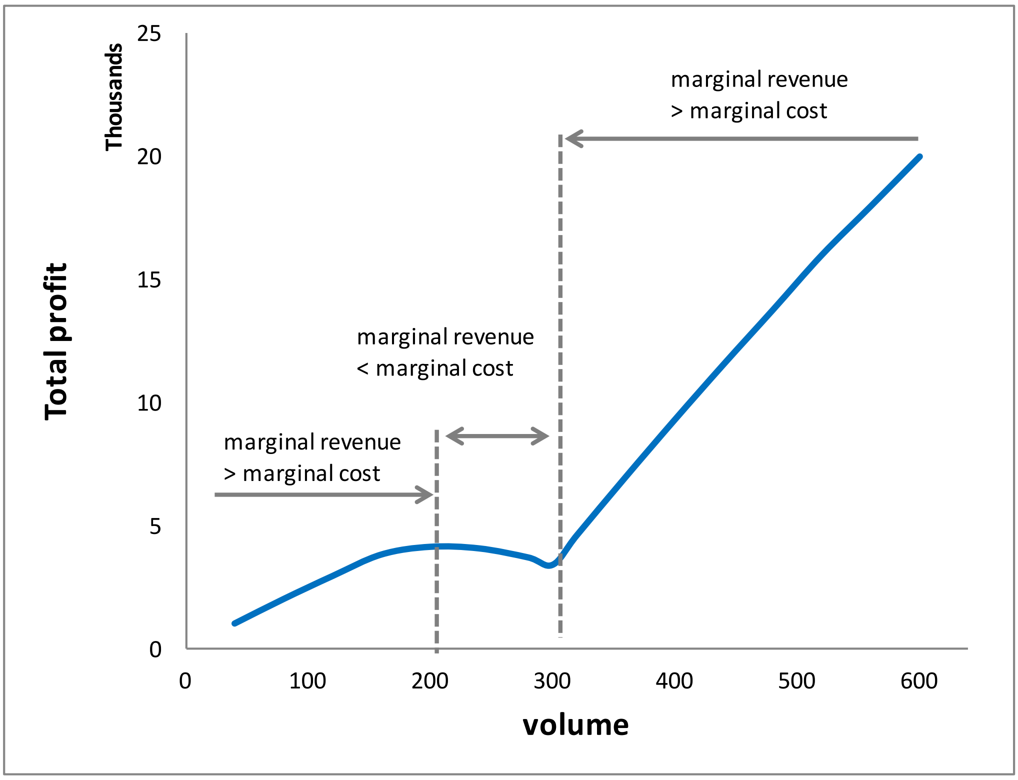

Fig. 3.11 Total profit at equilibrium

CHAPTER 4 PRICING DECISIONS WITH LIMITED INFORMATION

4.1 Introduction

Preliminary research on a game theoretic (GT) approach for pricing decisions by FFs has been reported in Chapter 3 . There has been very little existing research on pricing decisions, especially those by FFs who are the middlemen in a service chain involving shippers, FFs, and carriers. The work introduced a GT formulation to account for the willingness-to-pay of shippers and competition between FFs. It extended the 2-layer game formulation to a 3-layer game formulation, and used the concept of Nash equilibrium in an extensive form game and backward induction to determine optimal pricing decisions that maximize total profit in a decentralized manner.

However, like other analytical or quantitative analysis approaches, the GT approach requires very complex formulation. It also requires complete information of the system – e.g. shipper's willingness-to-pay, the rationality of each actor, or carriers' charging scheme. Although FFs can obtain this information by evaluating previous transactions or by conducting surveys, the results would have to be treated with a fair amount of scepticism because firms may not be willing to reveal such confidential information. Furthermore, the GT approach can only examine the interaction between players with similar decision making behavior rather than between actors with very different behaviors.

The aim of this chapter is to help a FF formulate its best pricing decisions when it has only limited information of the entire system. The information that is available to the FF is shown in Fig. 4.1. The FF knows its own objective, and can refer to its internal information (profit gain or loss, market share gain or loss, and whether quotations are accepted or not) to evaluate the performance of its previous actions so that future decisions can be improved. About shippers, the FF knows number of shippers and the demand of cargo movement. On carriers, this FF knows number of carriers, their full freight rate scheme, and capacity. However, the FF has no information on its competing FFs, and knows no more information other than mentioned above.

A Multi-Agent System (MAS) is built to investigate the interaction between the three parties so that the performance of each learning approach can be examined. Multi-agent simulations are conducted to investigate the interactions under various combinations of FFs that learn. This chapter would like to answer: 1) whether learning by trial and error can improve pricing performance; 2) which is the best learning mechanism; 3) how learning and pricing performance can be optimized. The critical parameters that determine learning performance as well as the best settings for these parameters are investigated as well.

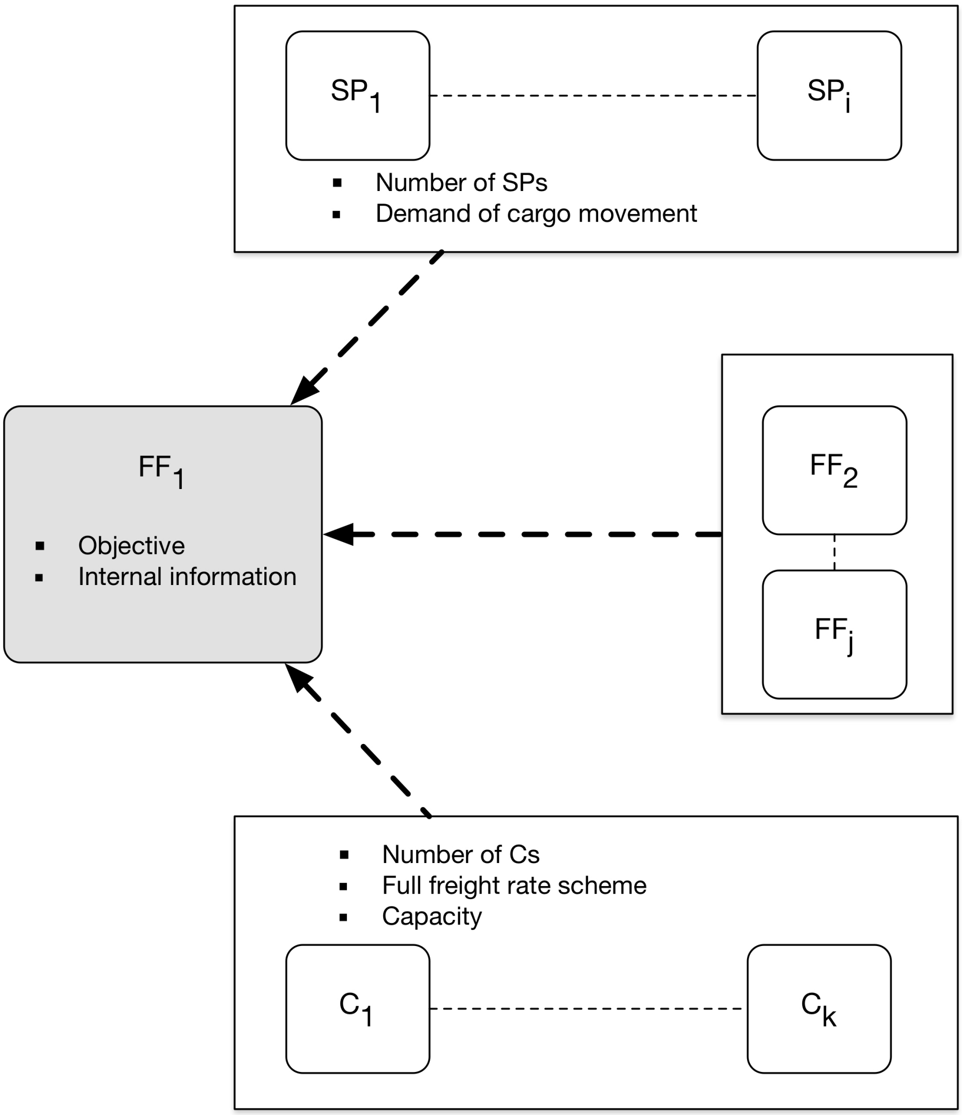

Fig. 4.1 A FF has limited information of the entire system

4.2 Formulation of FF's Pricing Decision

The formulation of a FF's pricing decision is within a context comprised of shippers ($SP_k, k = 1, .., K$), FFs ($FF_i, i = 1, \dots, I$) and carriers ($C_j, j = 1, \dots, J$) interacting over repeated transactions. As shown in Fig. 4.2, the first set of interactions occurs between shippers and FFs. Shippers first announce cargo volume and requirements to FFs. Then FFs quote charges and propose cargo transportation plans after making their pricing decisions. After comparing the quotations from all FFs, shippers offer their cargo to a preferred FF. The second set of interactions occurs between FFs and carriers. After receiving cargo from shippers, FFs consolidate and then split the cargo among carriers based on each individual carrier's pricing scheme and capacity. As shown in Fig. 4.2, learning is incorporated into the internal process of a FF: a learning model is first applied to examine the performance of decisions made in previous transactions. New pricing decisions are made with respect to acquired knowledge and the current pricing situation. This process of the FF pricing decision is repeated over many transactions in the market.

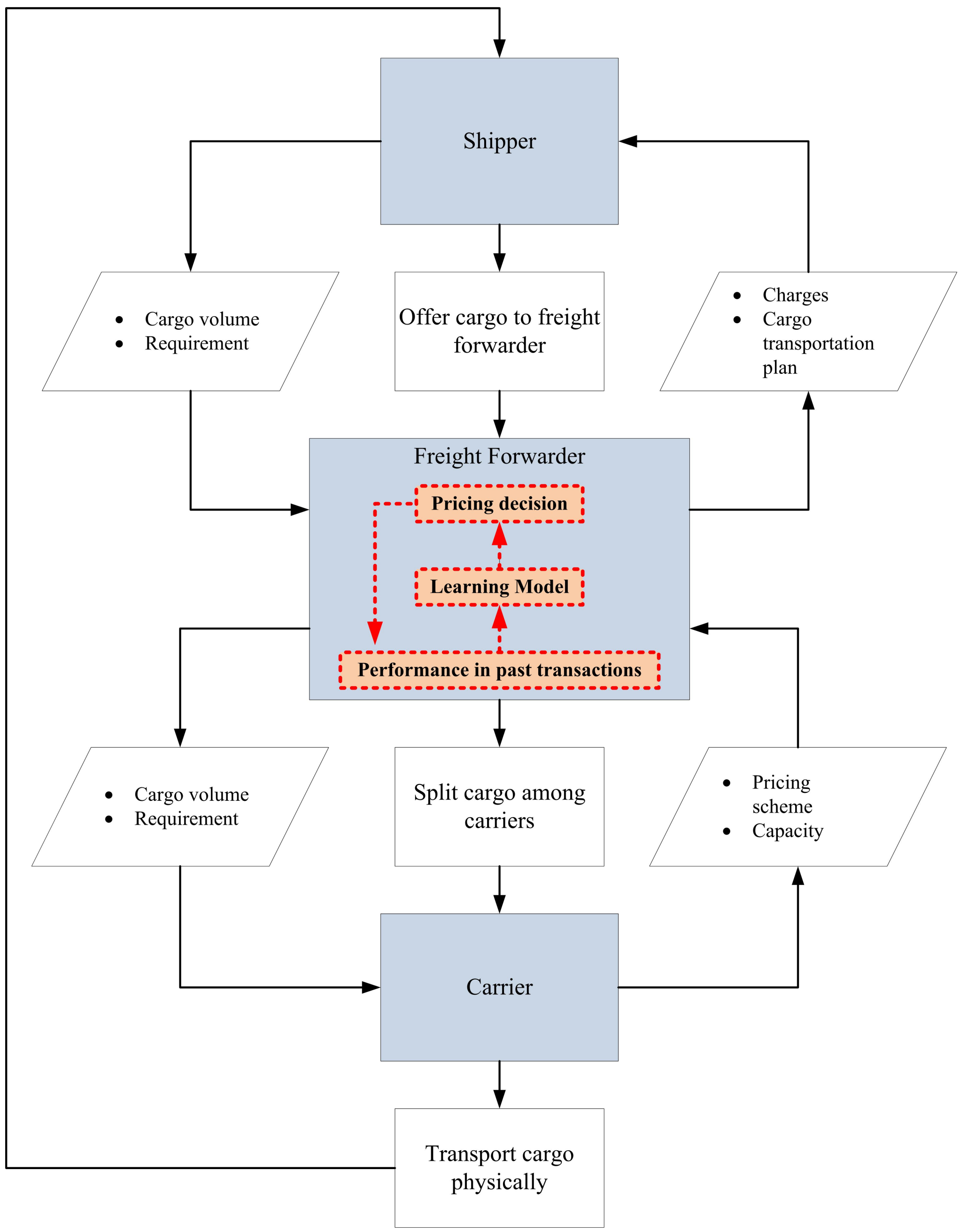

Fig. 4.2 Structure of interaction between shippers, FFs, and carriers

In order to formulate the charge to quote a shipper, a FF_i can make its pricing decisions as follows (as depicted in equation (4.1)):

- Step 1: estimate the lowest possible unit cargo movement cost that may occur by consolidating the cargo from all shippers – consolidated unit cost (CUC_i);
- Step 2: respond with a desired unit cargo movement charge PD_i to shippers by adding a desired markup pr_i to the estimate of the unit cost, which is the pricing decision made by FF_i.

$$PD_i = (1 + pr_i) \cdot CUC_i \tag{4.1}$$

The first key issue is how to estimate the potential consolidated unit cost (CUC_i). As FFs make use of existing available carriers in the spot market to earn the price difference, they can use the tariff schemes announced by different carriers to estimate a lower bound of this cost. The CUC_i to FF_i can be formulated as:

$$CUC_i = \frac{\pi F_i^{\ *}}{\sum_k V_k} \tag{4.2}$$

Where πF_i is the total cargo movement cost to FF_i when consolidating cargo from all shippers; $\pi F_i^{\ *}$ is the optimal value of πF_i, which is calculated by solving the following optimization model:

$$Min\ \pi F_i = \sum_j R_j(x_{ij})x_{ij} \tag{4.3}$$

Subject to:

$$\sum_j x_{ij} = \sum_k V_k \tag{4.4}$$

$$0 \leq x_{ij} \leq CA_j, \qquad j = 1,2,\ldots,J \tag{4.5}$$

The objective function minimizes the total fees paid to carriers (Equation (4.3)). Constraint (4.4) ensures that all cargo from shippers is transported. Constraint (4.5) ensures that the volume of cargo assigned to a given carrier is not beyond the carrier's capacity.

The other issue is how to set up a reasonable markup to recover the cost and maximize total profit. This pricing mechanism is called cost-plus pricing: the potential cost (CUC_i) is estimated first and then a markup (pr_i) is added in. Cost-plus pricing has the disadvantage of not being able to determine the unit cost if the final price has not been determined in the first place. Cost-plus pricing usually fails to account for the effect of price on volume and volume on cost, which leads to pricing decisions that undermine profits (Nagle et al., 2011). The result may be overpricing in weak markets and underpricing in strong ones - exactly the opposite of what is required of a prudent decision. Thus FFs should ask whether the change in price will result in a change in revenue that is more than sufficient to offset a change in total fixed and variable costs. In order to overcome the disadvantages of cost-plus pricing, FFs can make pricing decisions by incorporating learning so that a reasonable markup can be learned over time. They work on looking for the level of a reasonable markup to establish a prudent price. The price is determined in a strategic and profit-driven manner so that the profitability is guaranteed. The level of markup is learnt by evaluating the FFs' performance in previous transactions when different pricing decisions are made. FFs' own goals, the market condition, preferences of shippers, and the reactions of competitors can be considered when learning the markup level. FFs should learn to take actions that lead to the maximal net profits or the minimal net profits loss, rather than deal with the problem of pricing to cover costs.

In this research, we will consider three types of FFs: non-learning FFs, reinforcement learning (RL) FFs, and FFs learning on "If-Then (IT)" basis. The non-learning FFs fix their markup for a given time period with only periodic reviews. The other two types of learning are discussed in Sections 4.3.1 and 4.3.2.

4.3 Pricing decisions incorporating learning

4.3.1 Reinforcement Learning (RL)

In this chapter, RL approaches are implemented to help a FF adapt their pricing decisions over time. With RL, the FF is able to learn from its performance in previous interactions, and then use the knowledge to improve its future decisions.

A FF does not always have a model of the world because it lacks of information on what the market state will be after a specific pricing decision is made. The market condition is complex, and it is difficult for an individual firm to predict the direction of its evolution. In addition, a FF receives only the information of cargo volume and requirements from shippers. Then the FF is informed on the acceptance or rejection based on quoted price. On the other hand, through interacting with other parties, it is possible for a FF to gather internal and external information to measure the performance of its previous pricing decisions. As a result, the lack of a model of the world can be overcome by involving an function $Q(s_n, a_n)$, which is used as an evaluation of an action a_t carried in state s_t. The choice of the optimal decision is based on the following rule:

$$\pi^*(s_n) = \underset{a_n}{argmax}\, Q(s_n, a_n) \tag{4.6}$$

Where, the function $Q(s_n, a_n)$ can be defined as:

$$Q(s_n, a_n) = \max_{a_{n+1}, a_{n+2}, \cdots} (r_n + \gamma r_{n+1} + \gamma^2 r_{n+2} + \cdots) \tag{4.7}$$

Equation (4.7) maximizes the discounted reward starting from the next stage a_{n+1} rather than the current state a_n. Although a FF doesn't know exactly the function of $\delta(s_n, a_n)$ and r_n, it has to carry out an action a_n at the current stage s_n anyway. The agent will then know the successor state s_{n+1} and the reward r_n that will be received. Through trial and error, the FF is able to learn from its experience although it doesn't know the exactly the functions of $\delta(s_n, a_n)$. The function $Q(s_n, a_n)$ of a FF agent can be further expressed as:

$$\begin{aligned} Q(s_n, a_n) &= r_n + \gamma \max_{a_{n+1}, a_{n+2}, \cdots} (r_{n+1} + \gamma r_{n+2} + \cdots) \\ &= r_n + \gamma \max_{a_{n+1}} [r_{n+1} + \gamma \max_{a_{n+2}, a_{n+3}, \cdots} (r_{n+2} + \cdots)] \\ &= r_n + \gamma \max_{a_{n+1}} Q(s_{n+1}, a_{n+1}) \\ &= r_n + \gamma \max_{a_{n+1}} Q[\delta(s_n, a_n), a_{n+1}] \end{aligned} \tag{4.8}$$

Based on Equation (4.8), we know that:

$$Q^*(s_n, a_n) = r_n + \gamma Q^*(s_{n+1}, a_{n+1}) \tag{4.9}$$

As a result, a FF can learn the value of $Q(s,a)$ for all possible states $s \in \mathcal{S}$ and actions $a \in \mathcal{A}$by trial and error. As equation (4.9) can always be satisfied, the difference between the estimates of $Q(s_n, a_n)$ at two different times can be calculated as

$$\Delta_n = r_n + \gamma Q(s_{n+1}, a_{n+1}) - Q(s_n, a_n) \tag{4.10}$$

Theoretically, if the difference is small enough, we could conclude that the estimation is accurate. This is also the key idea of Temporal-Difference (TD). TD-learning methods use partial of the difference to update the estimate of $Q(s_n, a_n)$ at time n:

$$\alpha[r_n + \gamma Q(s_{n+1}, a_{n+1}) - Q(s_n, a_n)] \tag{4.11}$$

The step-size parameter $\alpha \in (0,1)$ influences the rate of learning, and determines how much the value of function $Q(s,a)$ is updated at each iteration.

In this research, four RL models are investigated: Action-Value Method, Softmax Method, SARSA Method (on-policy TD method), and Q-Learning Method (off-policy TD method). The first two methods are non-associative learning mechanisms because actions to be taken are not associated with the state. The latter two methods are associative learning mechanisms; they are also

Temporal-Difference (TD) learning methods. The details on the four RL models are presented from Section 4.3.1.1 to Section 4.3.1.4. These learning models are used by estimating the value of particular functions. By evaluating the functions of action, or state-action pairs, we are able to estimate how good it is for a FF to be in a given state, or how good it is to perform a given action in a given state:

- Function of action $Q(a)$: the mean reward that has been received when action a is selected;
- Function of state-action pairs $Q(s, a)$: the expected return starting from state s by taking action a;

4.3.1.1 Action-Value Method

The performance of a given action a is evaluated by the value of the action $Q_n(a)$. In this research, the action value is defined as the mean reward received when that action is selected (at the t^{th} play, action a has been chosen k_a times prior to time n, yielding rewards r_1, r_2, …, r_{k_a}):

$$Q_n(a) = \frac{r_1 + r_2 + \cdots + r_{k_a}}{k_a} \tag{4.12}$$

Then, the action selection rule is to choose in a greedy manner by selecting the action with the highest estimated value with a probability of

$(1-\varepsilon)$, which is called ε-greedy method. With a probability of ε, a random action is selected.

4.3.1.2 Softmax Method

The action with the highest mean reward is given the highest selection probability, and all the other actions are ranked and weighted accordingly. Thus, an action a is chosen with a probability of:

$$p_a = \frac{e^{\frac{Q_n(a)}{\tau}}}{\sum_{b \in A} e^{\frac{Q_n(b)}{\tau}}} \tag{4.13}$$

Where τ is called temperature - higher temperatures cause the actions to become more equally preferred. b is an arbitrary action within the action apace $\mathcal{A}$.

4.3.1.3 SARSA: an On-Policy TD Method

SARSA is short for State-Action-Reward-State-Action. The purpose of SARSA is to learn the state-action functions $\mathrm{Q(s,a)}$ for the current decision π for all states s and action a. FFs learn the $\mathrm{Q(s,a)}$ based on the pseudo code shows below:

Initialize *Q(s,a)* and s arbitrarily

Repeat (for each analysis period n):

Choose a based on s and $Q(s,a)$ for all $a \in A$ and $s=s$ (e.g., ε-greedy)

Take action a, observe r and the resulting state s'

Choose action a' in state s' based on $Q(s,a)$ for all $a \in A$ and s=s' (e.g. ε-greedy)

Update $Q(s,a)$ using: $Q(s,a) \leftarrow Q(s,a)+\alpha[r+\gamma Q(s',a')-Q(s,a)]$

$s \leftarrow s'$; $a \leftarrow a'$

Until N is reached

SARSA is an On-policy (decision) method as it attempts to evaluate or improve the policy (decision) that is used to generate actions.

4.3.1.4 Q-Learning: an Off-Policy TD Method

The state-action functions $Q(s,a)$ learned is independent of the action being followed, which simplifies the learning mechanism and guarantees early convergence. FFs learn the $Q(s,a)$ based on the pseudo code shows below:

Initialize $Q(s,a)$ and s arbitrarily

Repeat (for each analysis period n)

Choose a based on s and $Q(s,a)$ for all $a \in A$ and $s=s$ (e.g., ε-greedy)

Take action a, observe r, and the resulting state s'

Update Q(s,a) using: $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)$

$s \leftarrow s'$

Until N is reached

Q-learning is an off-policy method - the policy (decision) used to generate an action, called the behavior policy, may in fact be unrelated to the policy (decision) that is evaluated and improved, called the estimation policy.

4.3.2 Learning on If-Then (IT) Basis

If we use a six-player interaction with two actors in each tier (two shippers, two FFs and two carriers) as an example, a FF at time n can identify three possible states that it may currently be in (shown in Fig. 4.2). This FF can increase or decrease current markup by a certain amount, or stick to the current markup in the upcoming transactions.

Table 4.1 Possible states for a FF

Current state	Description
Unfavorable	Lost cargo from both shippers in the $(n-1)^{th}$ iteration
Acceptable	Gained cargo from only one shipper in the $(n-1)^{th}$ iteration
Favorable	Gained cargo from both shippers in the $(n-1)^{th}$ iteration

We further define parameter $ag_i \in [0,1]$ as a FF's aggressiveness associated with its pricing decision. FFs with a higher value for the aggressiveness parameter are more likely to lower markup when facing an unfavorable or acceptable state, and less likely to increase markup when facing a favorable state. ap_i is defined as the unit of markup adjustment by a FF. The rules for price adjustments with respect to a given ag_i are:

- In the favorable state: the probability to increase current markup pr_i by ap_i units equals $(1 - ag_i)$; whilst the probability to stick to current markup pr_i is ag_i;
- In the acceptable state: the probability to stick to the previous markup is $\left(1 - \frac{ag_i}{2}\right)$; whilst the probability to reduce pr_i by ap_i equals $\left(\frac{ag_i}{2}\right)$.
- In the unfavorable state: the probability to stick to the current markup pr_i is $(1 - ag_i)$; whilst the probability to reduce current markup pr_i by ap_i units equals to ag_i.

4.4 Multi-Agent System

A multi-Agent System (MAS) is built to investigate the interaction between shippers, FFs and carriers so that the performance of learning approaches proposed in Section 4.3 as well as their best settings for parameters can be examined. In the MAS, each player is represented as an intelligent agent. An agent is an entity which can perceive the environment and then reacts accordingly. The MAS is built from the bottom up by defining the behavior of each agent. Different agents are then put in an environment and allowed to interact. The performance of each agent as well as the behavior of the whole system will emerge out of the individual interactions.

The decision making procedure of an individual agent is represented by a statechart which is a visual construct that enables us to define event- and time-driven behavior of various agents (Borshchev, 2013). The statechart usually consists of states and transitions: a state is the "concentrated history" of the agent and also as a set of reactions to external events that determine the agent's future. A transition between states is triggered by a message, a condition, or a timeout, which also defines the reactions in a particular state or those when entering or existing a given state. When a transition is taken, the state may change and a new set of reactions may become active. State transitions are atomic and instantaneous.

MAS offers another way of looking at the whole system comprised of shippers, FFs, and carriers: we may not know how the system behaves as, what the key variables are and the dependencies between them, but we may have some insight into how agents in the system behave individually. We start building the model from the bottom up by identifying agents and defining their behaviors. Agents are connected to each other in an environment which may have its own dynamics (e.g. fluctuating level of demand or supply) and allowed to interact. The global behavior of the system emerges out of many individual behaviors that interact. An examination of the simulation results under different scenarios could help FFs improve their pricing decisions in future transactions.

4.4.1 Shipper Agent

The behavior of an individual shipper agent is defined by the statechart shown in Fig. 4.3. This shipper agent is first in the original state ("idle" state) if there is no cargo to be transported. Transition "t_1" is triggered once a demand of cargo movement is generated (the volume of cargo at hand is no longer zero). When exiting the "idle" state, the shipper agent sends solicitations to all FFs, and each solicitation comprises the volume of cargo. After sending the service request to all available FFs, the shipper agent enters the "requestsSent" state and waits for the responses from all contacted FFs. The shipper agent leaves the "requestsSent" state on 1) receiving quotations from all contacted FFs (transition "t_3" is triggered); or 2) receiving responses from at least one FFs (but not all FFs) but is no longer willing to wait for any further quotations (transition "t_2" is triggered). Before entering the "FF_selected" state, the shipper agent selects one FF by comparing all the received quotations. Each shipper agent has its own selection procedure, and these procedures may vary among different shippers. A shipper agent may rank all the received quotations with respect to its goals and expectations, and then make a decision. It may also use optimization procedure to maximize its goals or utility. After selecting the preferred FF, the shipper agent enters the "FF_selected" state, and all the cargo is delivered to the selected FF. Then the transition "t_4" is triggered, and the shipper enters the "Idle" state again and waits for the next cycle of interaction with FFs.

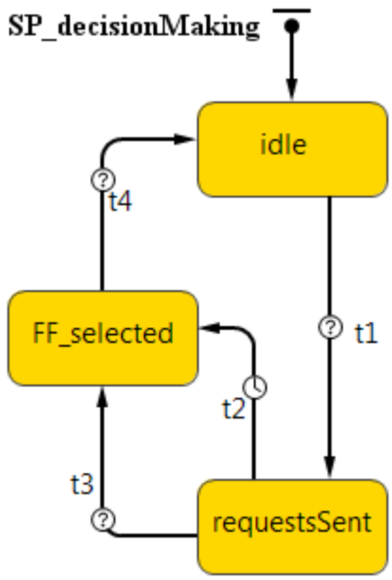

Fig. 4.3 Shipper agent's statechart

4.4.2 FF Agent

The statechart of a FF agent is divided into two blocks: the first block (Fig. 4.4) represents the interaction with shipper agents; the second block (Fig. 4.5) represents the interaction with carrier agents.

In Fig. 4.4, a FF agent starts in the "idle_SP" state if no shipper has contacted it for logistics services. Transition "t_1" is triggered once the FF receives a solicitation from any shipper. After receiving the solicitation, the FF leaves the "idle_SP" state and enters the "requestReceived" state. It will start estimating the potential cost for the current request. Different FF agents have their own way of cost estimate, and they may or may not consider the consolidation of the cargo from different shippers with the cargo from previous transactions that is still being processed. The FF agent performs it cost estimation within a specified time interval, and then the transition "t_2" is triggered. The FF agent enters the "costEstimated" state and starts preparing a quotation to the shipper. Again, after a given time interval, the FF agent sends the quotation back to the shipper. Then transition "t_3" is triggered, and the statechart enters the "quotationSent" state. In the end, the statechart returns to the original "idle_SP" state.

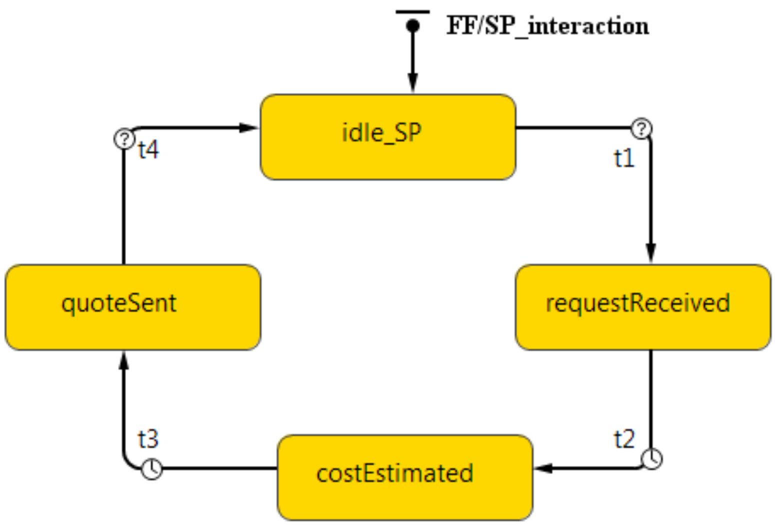

Fig. 4.4 FF agent's statechart - interacting with shipper

A FF's interaction with carriers is represented as the statechart shown in Fig. 4.5. A FF agent starts in the "idle_C" state when no cargo needs to be processed or assigned to carriers. Transition "t_5" is triggered and the statechart enters the "cargoToBeSplit" state once new cargo is received from shippers. The FF agent waits in this state until there is one or more available carrier that can transport the cargo. If there is at least one available carrier, the transition "t_6" will be triggered. The FF agent leaves the "cargoToBeSplit" state and starts designing a cargo split plan by making the best combination of available carriers. After finalizing the cargo split plan, the FF agent will send the request to each selected carrier individually. Different FF agents may have different considerations or goals when they design their cargo split plans. After all the requests are sent, the FF agent enters the "splitRequestsSent" state and will be waiting for confirmation from all carriers contacted. The transition "t_8" will be triggered if all the requests to carriers have been responded (either accepted or rejected). Otherwise, the transition "t_7" is triggered if the FF agent received response from at least one carrier (but not all contacted carriers). After leaving the "splitRequestsSent" state, the FF agent will assign cargo to carriers. The statechart then enters the "requestsConfirmed" state. If there is still remaining cargo or new cargo has been received from shippers, transition "t_9" will be triggered, and the statechart goes to the "cargoToBeSplit" state; otherwise transition "t_{10}" will be triggered and the statechart will return to the originating state – "idle_C" state.

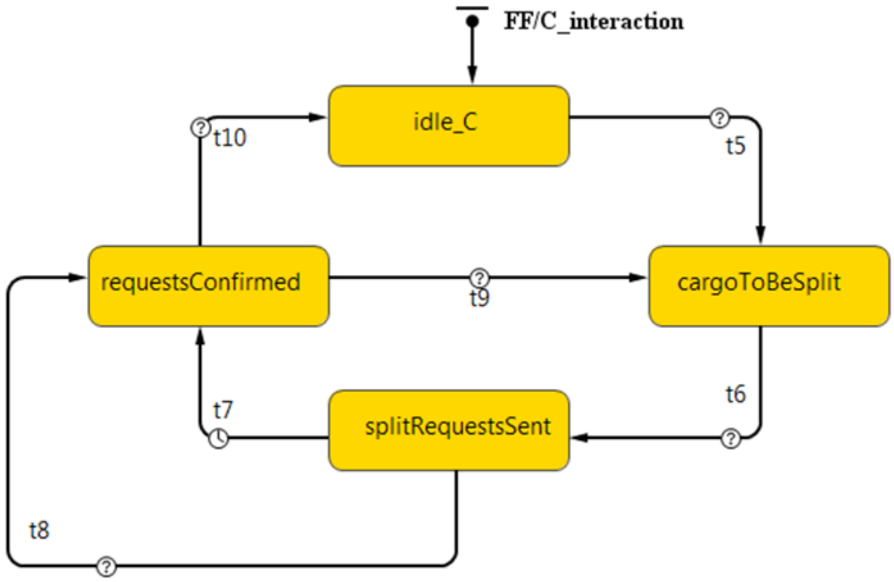

Fig. 4.5 FF agent's statechart - interacting with carrier

4.4.3 Carrier Agent

The statechart of a carrier agent is depicted in Fig. 4.6. The originating state is the "available" state in which the carrier agent becomes available to transport cargo physically for one or more FFs. Transition "t_1" is triggered if there is at least one request received from FFs. The statechart then enters the "requestGathering" state in which the carrier agent will waits to collect further requests before making a decision regarding which FF to serve. Transition "t_2" is triggered if all FFs canceled their requests, and the statechart will then go back the originating "available" state. Transition "t_3" is triggered if the carrier agent has been in the "requestGathering" state for enough time and is not willing to wait any further. After leaving the "requestGathering" state, the carrier agent will select one or more requests among all the active requests (requests that have been received during the "requestGathering" state but have not been canceled by FFs yet). After determining the FFs to be served in the next trip, the carrier agent enters the "transporting" state in which the carrier agent transports the cargo from the origin to the destination. Transition "t_4" is triggered if the carrier agent's cargo movement task is completed and the carrier agent is again available for the next assignment.

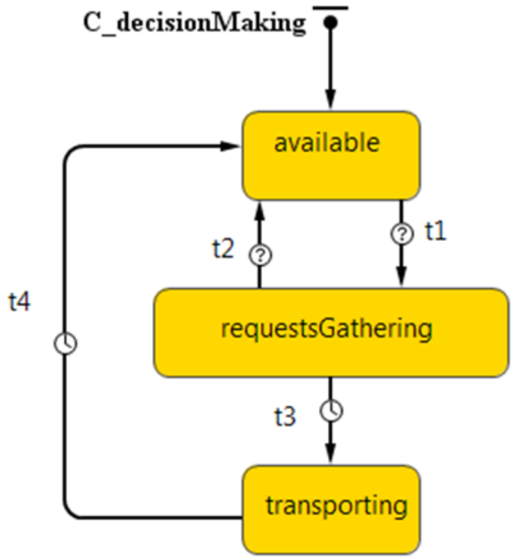

Fig. 4.6 Carrier agent's statechart

4.5 Experiments and Simulations

The purpose of conducting multi-agent simulation is to investigate whether learning from previous transactions can lead to better freight pricing decisions for FFs. Which is the best learning mechanism, and how learning and pricing performance can be optimized are also questions we would like to answer. The critical parameters that determine learning performance as well as the best settings for these parameters are investigated as well. By using the multi-agent system built in Section 4.4, pricing performance of the learning mechanisms proposed in Section 4.3 is examined. Multi-agent simulations are conducted to investigate the interactions between various combinations of FFs that learn. The pricing decisions that emerge out of multi-agent simulation are also compared with those solved by the GT approach presented in Chapter 3 .

4.5.1 Experiment Settings and Assumptions

The experiments in this chapter are conducted within a similar context as Section 3.4. Two shippers want to move containers from city A to city B. Each shipper is going to outsource its vehicle movement tasks to a FF. There are two FFs in the market, and they are available to both shippers. Two vessels (carriers) serve the route from city A to city B, and both FFs are going to make use of these two carriers to design their cargo transportation plans. All the other features of the three-tier interaction between shippers, FFs, and carriers remain unchanged as shown in Fig. 3.3.

Further in this chapter, the total analysis horizon is divided into N analysis periods. Within each period n, FFs first obtain cargo from shippers and then split the cargo received among carriers. After the carriers move the cargo from the origin to the destination, the simulation time is advanced to time $n+1$. The previous steps are repeated until the final analysis period N is reached.

We define all the interactions that happen during the period n as the n^{th} iteration.

For each iteration, the two shippers (SP_1 & SP_2) need to transport $V_1 = 250$ TEUs and $V_2 = 200$ TEUs respectively, and the two carriers (C_1 & C_2) can both provide slots for $ca_1 = ca_2 = 300$ TEUs. $SP_k(\, k = 1{,}2)$ will independently choose one FF by comparing the proposed unit price from the two FFs, denoted as $PD_i, (\, i = 1{,}2)$.

Within each iteration, the total capacity of both carriers is more than enough to meet the demand from both shippers simultaneously - there is oversupply in the market. The demand from shippers and the supply from carriers are fixed. All carriers are using downward linear pricing schemes, and they will prefer the FF with the higher volume of cargo offered. The value of parameters for carriers is shown in Table 4.2 (the same as applied in Chapter 3 , Fig. 3.4)

Table 4.2 Parameters for carrier agents

	a_j	b_j	Capacity of C_j	Preferred FF	Pricing scheme
Carrier 1	800	0.5	300	FFs with higher cargo volume	$y = a_j - b_j x$;
Carrier 2	600	0.3	300	FFs with higher cargo volume	

The interaction between the two shippers ($SP_k, k = 1,2$), two FFs ($FF_i, i = 1,2$), and two carriers ($C_j, j = 1,2$) is investigated by conducting multi-agent simulations. The goal of each FF is to maximize total profit. The markup pr_i of either FF is allowed to vary in the range of [0,30%] in increments of 1%. As both FFs are NVOCCs, they will depend on carriers to design the cargo movement plans. They have no direct information on the pricing decisions made by their rival, or how their rival's behaviors adapt over time other than whether their bids were successful or not. Each FF, at time n, can identify three possible states that it may be in before taking further action – favorable, acceptable and acceptable states (Table 3.1). The greedy value ε is set to be 0.05. The ap_i in the if –then model is set to 1%.

For each combination of FFs, the experiment is run 20 times with each run lasting 500 iterations. The performance at a given time n is evaluated using the following indicator:

$$Total\ profit_n = \sum_{1}^{n} Profit_n \tag{4.14}$$

The reward r_n is quantified as the profits earned within iteration n after taking action a_n:

$$r_n = Profit_n \tag{4.15}$$

There is no other interaction between any pair of players other than that described, and the influence of long term contracts is not considered for the moment.

4.6 Experiment 4a: Effect of RL on Pricing Decision

The aim of conducting Expt. 4a is to investigate the effect of reinforcement learning on FF's pricing decision. An experiment was conducted where one FF agent learned to adjust its markup by executing one of the four RL models ("challenger", designated as FF_1), while the other FF used a fixed markup of 15% ("defender", designated as FF_2). Both shippers prefer the FF who offers the lowest price. Settings for carriers remain unchanged as shown in Table 4.2.

An extensive search was conducted to find the optimal setting for the parameters associated with each of the four learning models used by the challenger (shown in Table 4.3). The performance (averaged over 20 runs of 500 iterations each) of the challenger and the defender under the best settings of parameters is shown in Fig. 4.7. We conclude that any one of the reinforcement learning models helps improve a FF's pricing performance vis-a-vis a fixed markup competitor.

Table 4.3 Optimal setting for model parameters (RL vs. non-learning)

RL model	Optimal setting
Action-value	$\varepsilon = 0.05$
Softmax	$t = 500$
SARSA	$\varepsilon = 0.05, \alpha = 0.5, \gamma = 0.05$
Q-learning	$\varepsilon = 0.05, \alpha = 0.5, \gamma = 0.05$

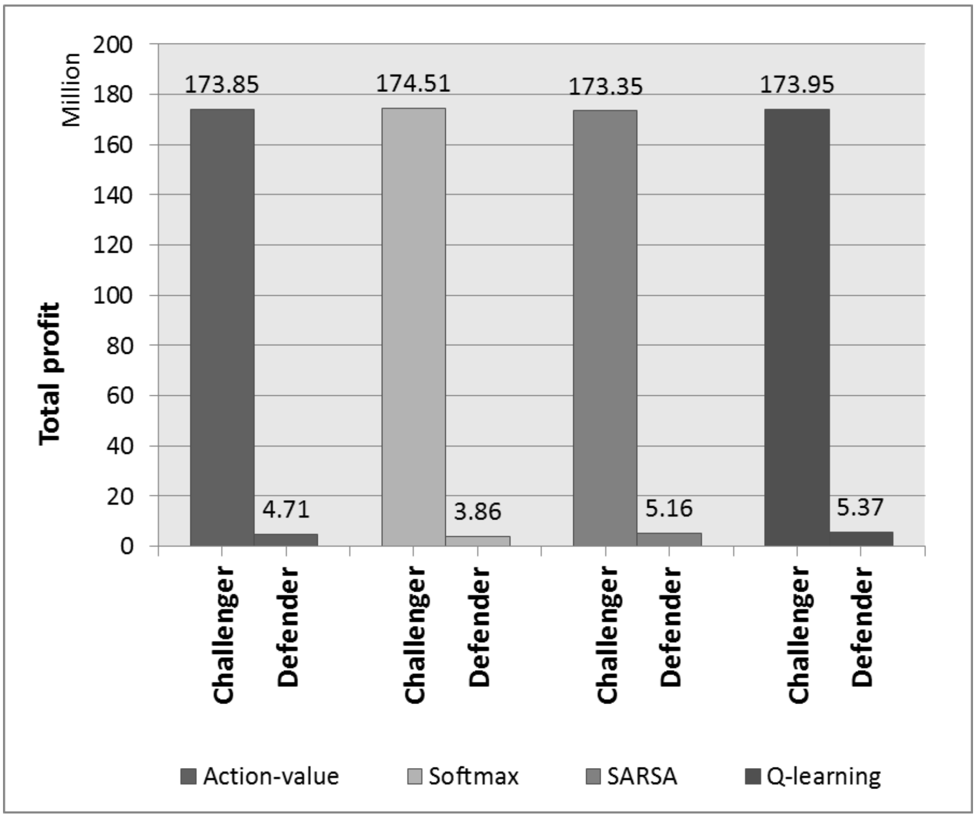

Fig. 4.7 Pricing performance –RL challenger against 'no learning' defender

By examining a particular experimented run (shown in Fig. 4.8), we observe that it takes fewer iterations to learn a near optimal action using the Softmax model, slightly more iterations via the SARSA or the Q-learning, and the most number of iterations by the Action-value model. In the beginning, the average profit per iteration is higher for the Softmax model but increases very slowly afterwards. On the other hand, although the average profit per iteration is lower at the beginning for both SARSA and Q-learning, the profit increases significantly after several more iterations. SARSA and Q-learning also help the challenger learn an optimal action in a timely manner.

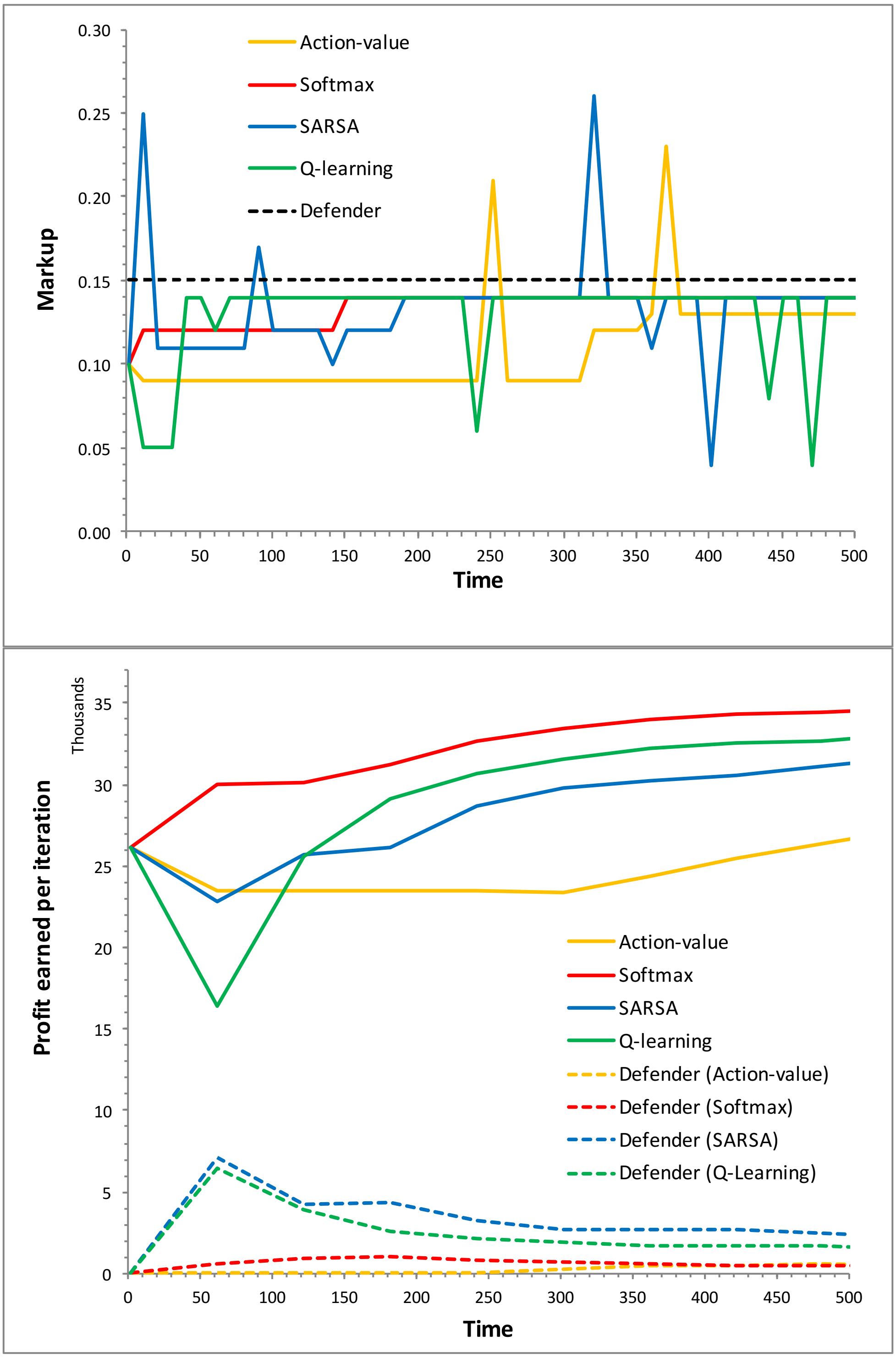

Fig. 4.8 Learning performance –RL challenger against fixed markup defender

4.7 Experiment 4b: RL Pricing Decision vs. GT Equilibrium Pricing Decision

The aim of conducting Expt. 4b is to compare the optimal pricing decisions obtained by using one of the four RL models through multi-agent simulations (RL pricing) with those obtained by solving an analytical mode – GT model (GT equilibrium pricing). For both MAS and GT approaches, we use the same six-player interaction of two shippers, two FFs and two carriers (as introduced in Section 4.5.1). Settings for the experiment remain unchanged (as introduced in Section 4.5.1) except for the following:

1) Both shippers make decisions based on the multinomial logit (MNL) model, and the selection behavior of a shipper is determined by its utility function (described in Section 3.3.2.2).
2) Both shippers' price sensitivity varies within $[0.005, 0.05]$.
3) The maximum markup of both FFs is allowed to vary in the range of [100%,600%].

The RL pricing decisions are obtained by running multi-agent simulations. Both FFs learn using the same RL model. The discussion in later sections will be based on the SARSA method because as shown in Fig. 4.7 there is little difference in the pricing performance of these four RL models. In order to quantify the performance of RL pricing, the following indicators are calculated for each FF at the final iteration $N = 500$:

$$RL\ \ unit\ profit\ = \frac{\sum_{n=1}^{N} Total\ profit\ in\ iteration\ n}{\sum_{n=1}^{N} Volume\ of\ cargo\ gained\ \ in\ iteration\ n} \quad (4.16)$$

$$RL\ price\ = \frac{\sum_{n=1}^{N} Revenue\ in\ iteration\ n}{\sum_{n=1}^{N} Volume\ of\ cargo\ received\ \ in\ iteration\ n} \quad (4.17)$$

$$RL\ \ unit\ cost\ = \frac{\sum_{n=1}^{N} Total\ cost\ in\ iteration\ n}{\sum_{n=1}^{N} Volume\ of\ cargo\ gained\ \ in\ iteration\ n} \quad (4.18)$$

$$RL\ \ markup\ = \frac{RL\ \ unit\ profit}{RL\ \ unit\ cost} \quad (4.19)$$

$$RL\ \ volume = \frac{\sum_{n=1}^{N} Volume\ of\ cargo\ received\ \ in\ iteration\ n}{N} \quad (4.20)$$

The analytical model refers to the GT approach described in Chapter 3 . SP_k's utility when selecting FF_i is defined by its utility function $U_{ki} = v_{ki} + \varepsilon_{ki}$, where v_{ki} is the systematic components of U_{ki}, and ε_{ki} is the random part. The deterministic part of U_{ki} is defined as $v_{ki} = \alpha_k - \beta_k PD_i$, where PD_i is the pricing decision of FF_i, and α_k and β_k are positive constants associated with SP_k's tastes when selecting a preferred FF. β_k reflects SP_k's sensitivity towards price. Both shippers are assumed to have the same price sensitivity ($\beta_k = \beta_{\underline{k}}$).

The GT equilibrium pricing decisions are the best options for both FFs given the information they possess. No one has the incentive to deviate from the current situation because deviation will not make them better off.

4.7.1 Effect of Price Sensitivity and Action Space on Pricing Decision

This section examines the effect of shippers' price sensitivity and FFs' action space on the pricing decisions by FFs. Fig. 4.9 plots the RL unit profit and the GT equilibrium unit profit against shippers' price sensitivity, which confirms that there is an inverse relationship between unit profit and shippers' price sensitivity. An inverse relationship can be found between: 1) markup and price sensitivity (Fig. 4.10) and 2) price and price sensitivity (Fig. 4.11). As a result, a FF can be better off by proposing charges with respect to the price sensitivity of clients.

In addition, a FF's action space will affect the RL unit profit learned through the interactions (Fig. 4.9). The larger the action space is the further the RL unit profit will be from the GT equilibrium unit profit because a larger action space requires more actions to be evaluated before a FF can find the optimal price. As RL is conducted on a trial and error basis, there are more actions to evaluate if the maximum markup is larger (600%) compared with the situation when the maximum markup is limited (100%). Similar conclusions can be obtained by examining the RL markup (Fig. 4.10) and RL price (Fig. 4.11).

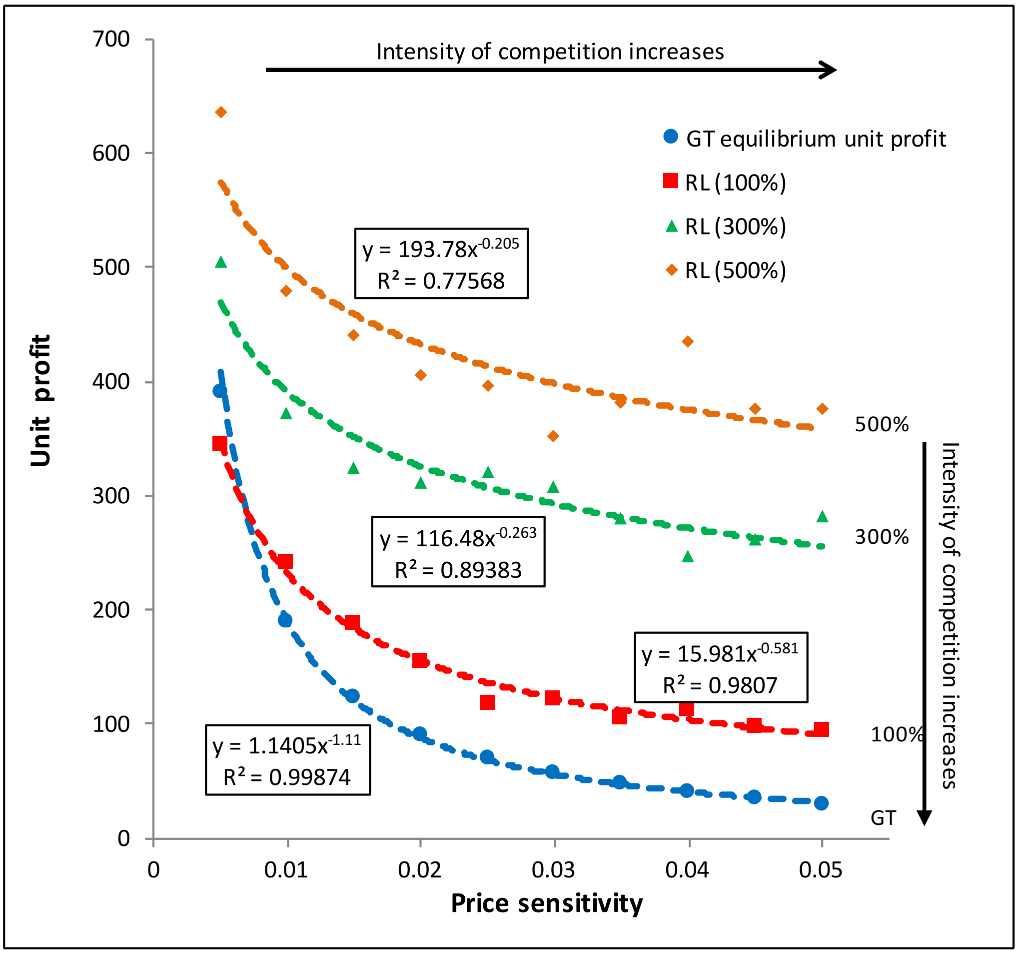

Fig. 4.9 Unit cargo profit - RL (SARSA) & GT approach

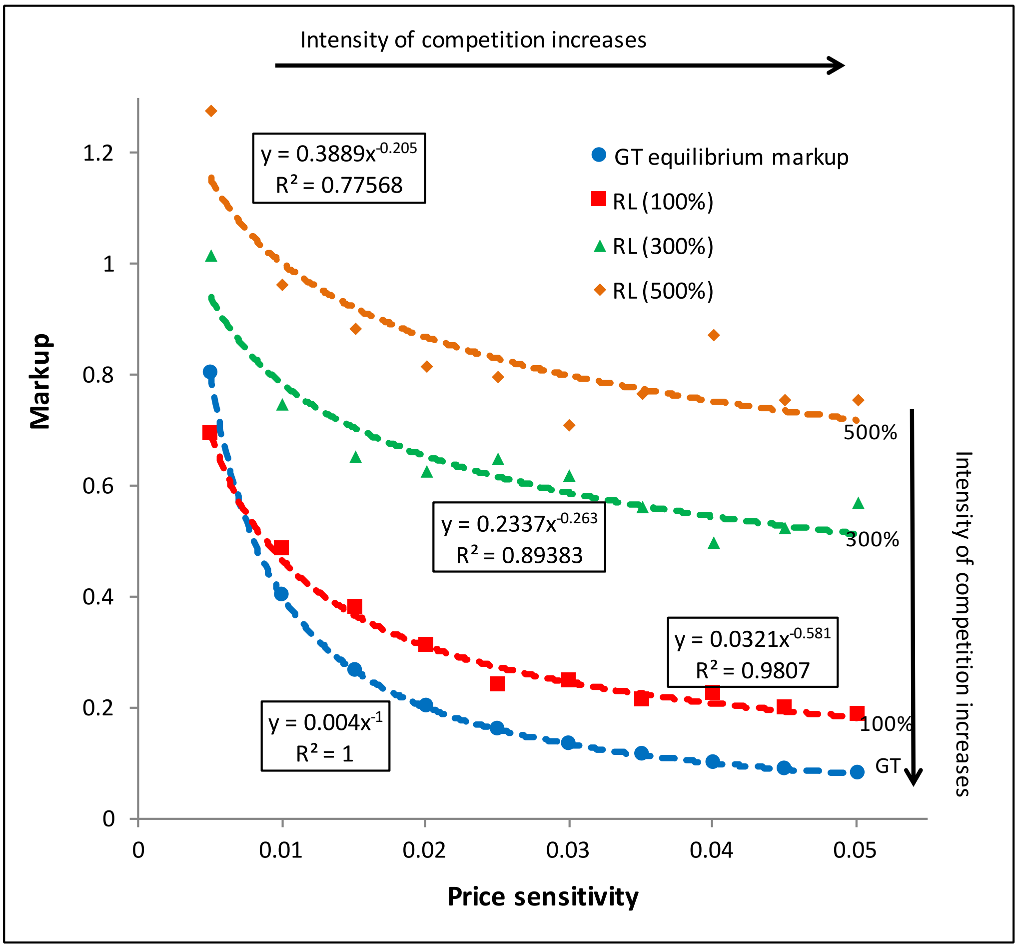

Fig. 4.10 Markup - RL (SARSA) & GT approach

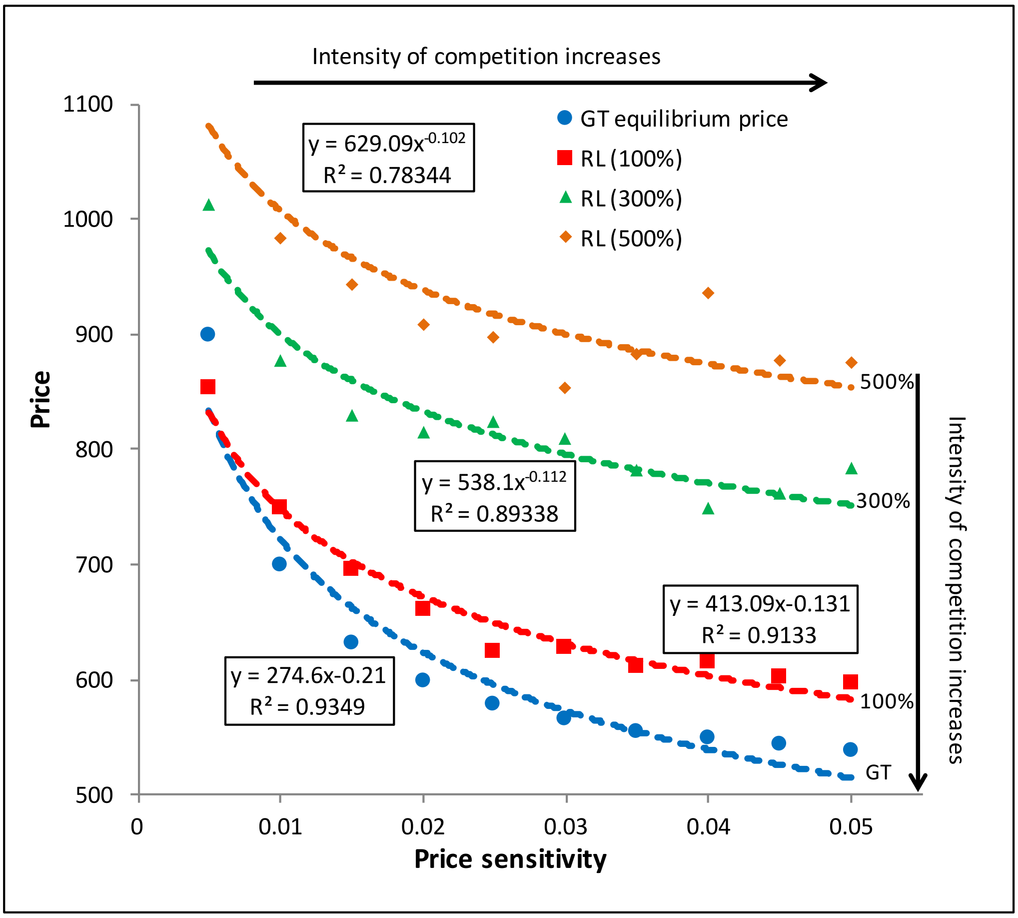

Fig. 4.11 Unit cargo price - RL (SARSA) & GT approach

4.7.2 Effect of Number of Iterations and Level of Information on Pricing Decision

This section examines the effect of number of iterations and FFs' level of information on the pricing decisions by FFs. Fig. 4.12 plots RL price obtained after 500 and 5000 iterations when the maximum markup is 600%, which confirms that the RL price is below the maximum possible price (the price formulated using the maximum markup, which equals to SGD 3556) and above the GT equilibrium price throughout all simulations. More specifically, the RL price curve is always between the expected random price curve (the expected price if a FF randomly chooses one price within its action space) and the GT equilibrium price curve. This is because the GT equilibrium price is optimal given that a FF has the complete information of the whole system (shippers' utility function, carriers' decision making procedure, and how each player interacts with the other). The expected random price is formulated when a FF knows nothing about the system – the FF randomly chooses one markup from its action space. For the RL price, a FF has limited information – whether quotations are accepted, profit and market share gain etc.. Furthermore, the more iterations it takes, the closer the RL price converges to the GT equilibrium price - the RL price achieved after 5000 iterations is closer to the GT equilibrium price than that obtained after 500 iterations.

When the allowable markup is significantly decreased from 600% (Fig. 4.12) to 100% (Fig. 4.13), the RL price still does not reach the GT equilibrium price no matter how many more iterations are run. These two figures also show that the difference between the RL price and the GT equilibrium price grows with respect to shippers' price sensitivity.

The results suggest that a FF should be aware of how the level of information and number of iterations will affect the pricing performance of competitors and itself so that an optimal decision can be obtained after as fewer interactions as possible.

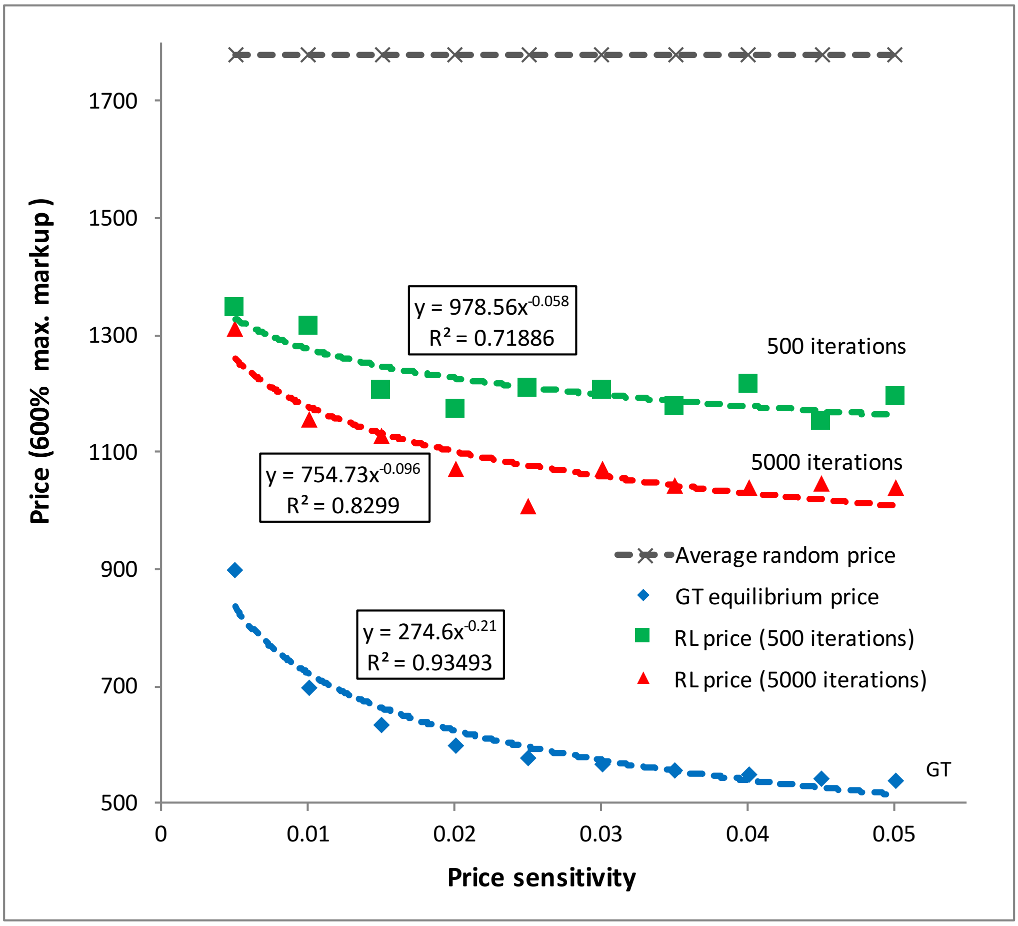

Fig. 4.12 RL price (maximum markup 600%) vs. GT equilibrium price

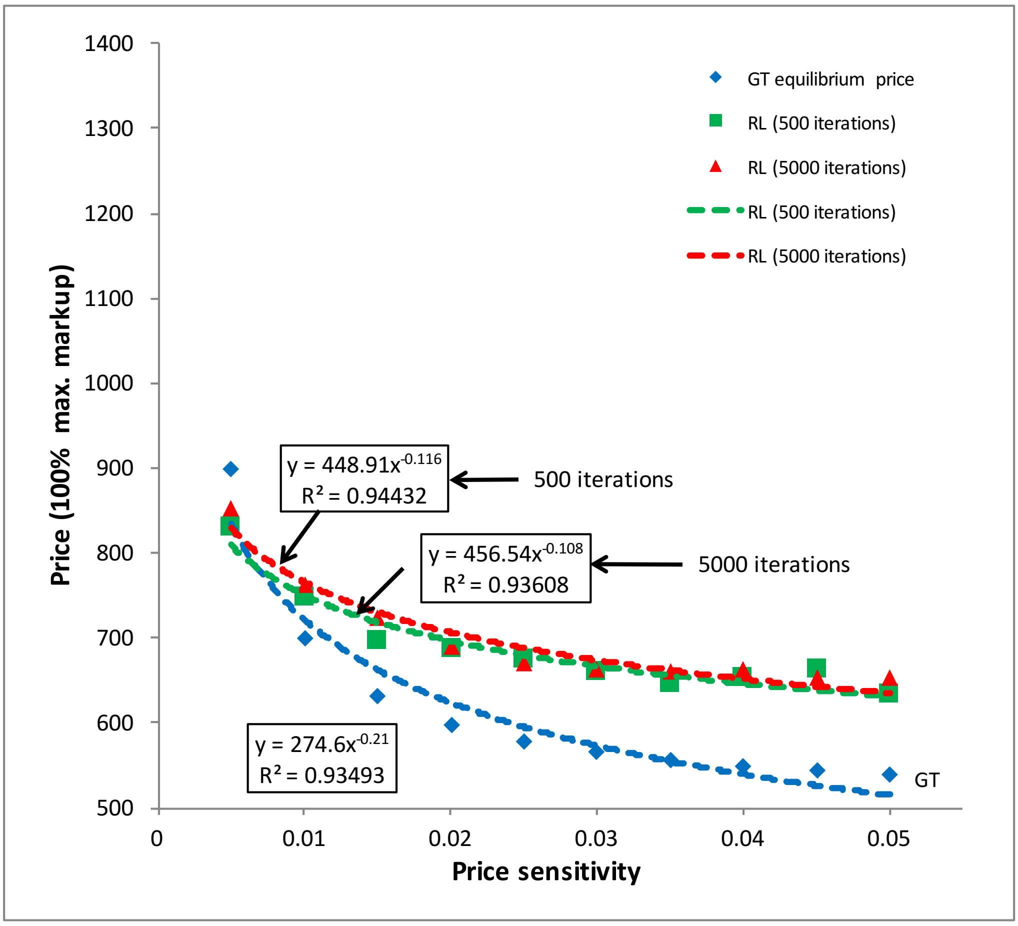

Fig. 4.13 RL price (maximum markup 100%) vs. GT equilibrium price

4.7.3 Effect of Price Sensitivity on Unit Cargo Cost

This section examines the effect of shippers' price sensitivity on FFs' unit cargo cost. The GT equilibrium unit cost, the RL unit cost (equation (4.18)), and the lowest possible unit cost are plotted in Fig. 4.14. The lowest possible unit cost is calculated by consolidating all cargo from shippers. First of all, the RL unit cost curves are all above the lowest possible per unit cost and below the GT equilibrium unit cost. In addition, the more price sensitive the shippers are, the closer the RL unit cost converges to the lowest possible per unit cost; while the less price sensitive the shippers are, the closer the RL unit cost is to the GT equilibrium unit cost. This is because when shippers are price sensitive, the FF who offers the lower price is more likely to obtain cargo from both shippers. This FF can make use of the economy of scale, and the cost converges to the lowest possible. When shippers are less price sensitive, the RL unit cost approaches the GT unit cost. The latter is higher than all RL units costs established, and much higher than the lowest consolidated cost. GT equilibrium unit cost are therefore not the lowest, and shippers can benefit from competition.

The investigation of these different measures of cost is critical for FFs' practical operations because these costs are the basis on which FFs formulate charges or learn an optimal markup. FFs can also know the effect of their action space, demand level, and shippers' price sensitivity on the potential cost so that a better estimate of the operating cost can be made.

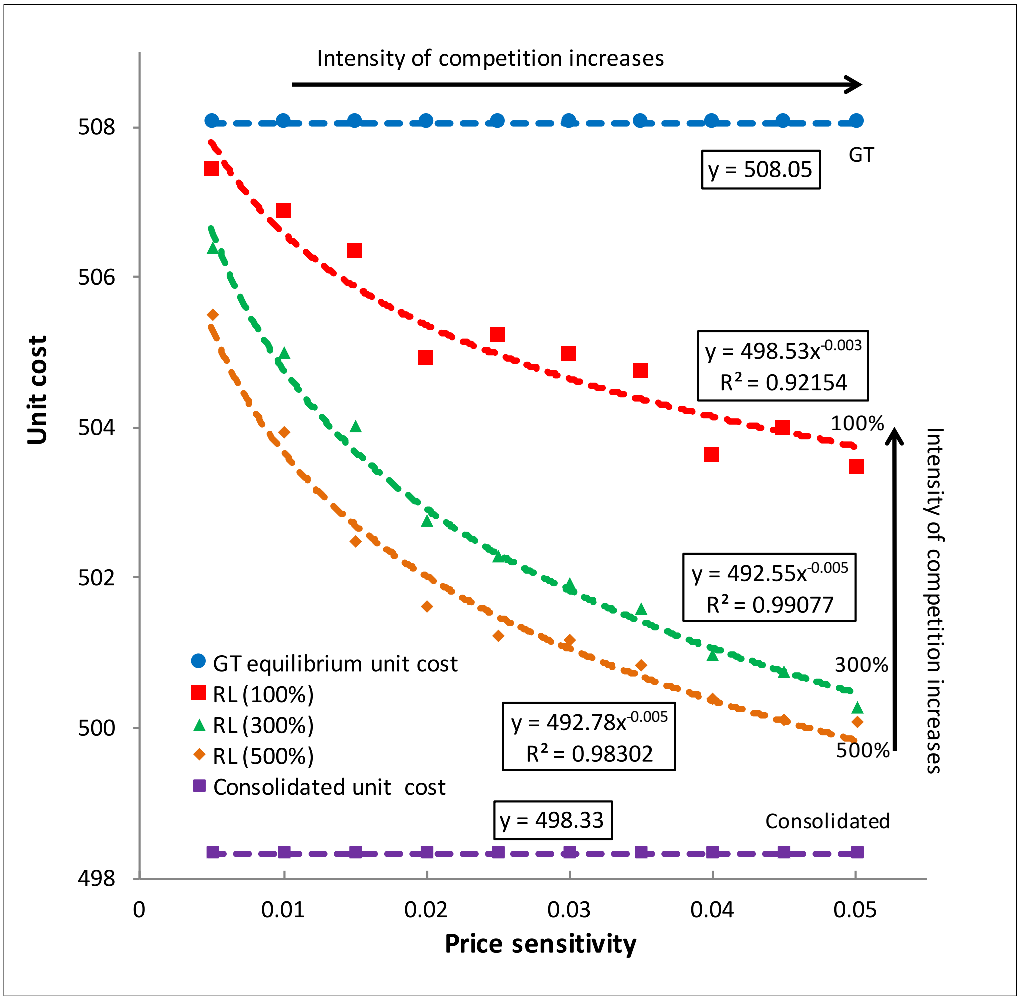

Fig. 4.14 Unit cargo cost - MAS (SARSA) & GT approach

4.7.4 Effect of Price Sensitivity on Volume of Cargo Obtained

This section examines the effect of shippers' price sensitivity on FFs' volume of cargo obtained. Fig. 4.15 shows the MAS equilibrium cargo volume (equation (4.20)) and the GT equilibrium cargo volume. We conclude that the MAS equilibrium volume matches the game theoretic equilibrium cargo volume, although the MAS equilibrium volume varies a little bit from the game theoretic equilibrium cargo volume without any definite trend with regards to the price sensitivity of shippers or the FF's action space.

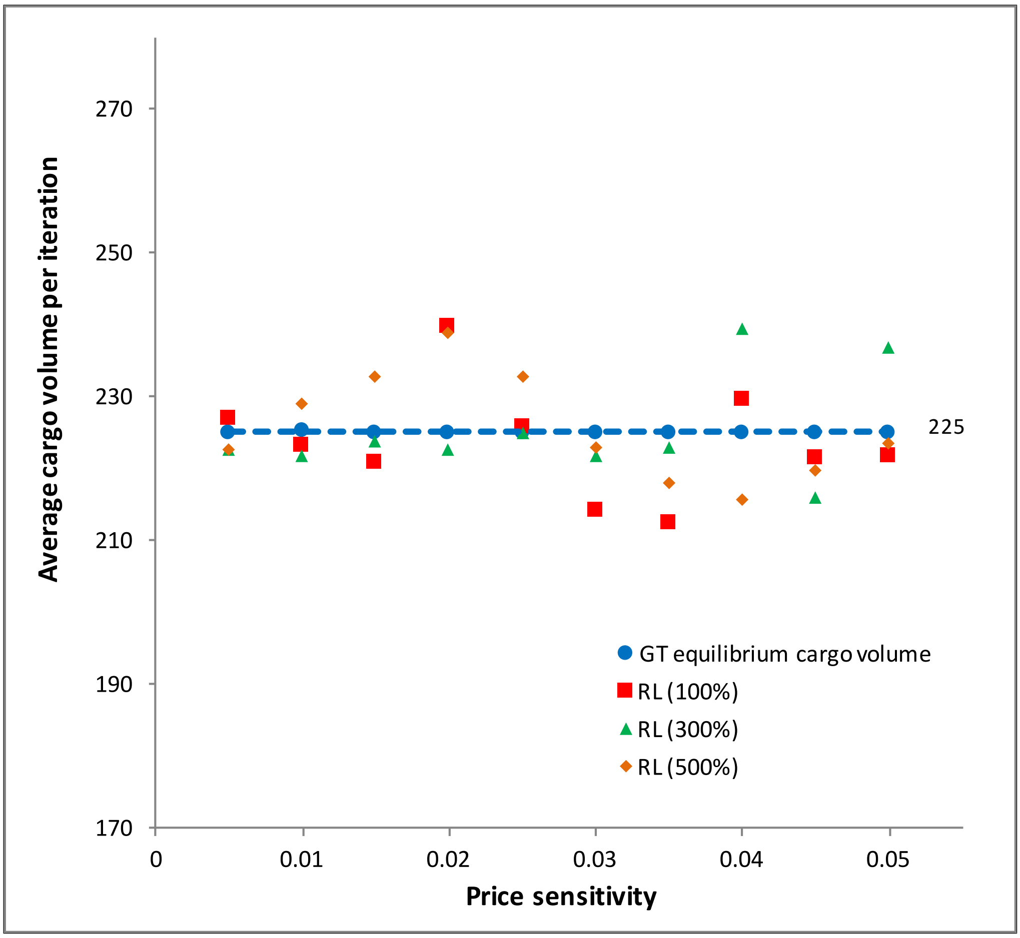

Fig. 4.15 Average cargo volume - MAS (SARSA) & GT approach

4.7.5 Effect of level of Competition Intensity on Pricing Performance

This section examines the effect of level of competition on FFs' pricing performance. Two forces intensify the level of competition in the market from the FFs' perspective – shippers' high price sensitivity (vertical force on the intensity of competition, V-Force) and competitors' high intelligence (horizontal force on the intensity of competition, H-Force).

The V-force of a FF is caused by its vertical interactions with shippers: if shippers are more sensitive on price, the FF have to quote lower prices so as to beat competitors and secure cargo. Thus, the level of competition in the market will be more intensive if the V-force is higher. As the V-force makes shippers more sensitive regarding price, FFs have to quote a lower price so as to beat competitors and secure cargo.

The H-force of a FF is caused by its horizontal competition with competing FFs. Competitors' high intelligence makes competitors learn and adapt very quickly so that the FF will not prevail in competition all the time. Thus, the level of competition in the market will be more intensive is the H force is higher. The H-force makes competitors learn and adapt very quickly so that a particular FF will not prevail in competition all the time.

Fig. 4.9 shows that the V-Force undermines RL unit profit earned by FFs – there is inverse relationship between shippers' price sensitivity and unit profit. On the other hand, the H-Force in this research is determined by FFs' action space – a smaller action space makes FFs learn faster and thus appear to be more intelligent. FFs using RL learn and respond faster when the maximum allowable markup is 100% compare with the situation when this markup is 600%. Fig. 4.9 shows the H-F also drives down the RL unit profit earned by FFs – there is an inverse relationship between unit profit and maximum allowable markup.

Similar conclusions can be drawn when we examine RL markup (Fig. 4.10) and RL price (Fig. 4.11). The above discussion indicates that a high intensity of competition undermines pricing performance of FFs but benefits shippers. In Fig. 4.16, the poor pricing performance of if-then FF and Softmax FF is also because of the high intensity of competition: both FFs learn very efficiently. Fig. 4.14 shows that the intensity of competition has two effects on FFs' unit cost. The V-Force drives down unit cost to the consolidated price, while the H-Force increases unit cost to the GT equilibrium cost. The former makes a FF more likely to gain all the cargo from shippers, while the latter makes two equally competitors match each other more quickly and thus split cargo and profit evenly. The discussions show that the intensity of competition has two effects on FFs' cost: 1) the V-Force benefits FFs but undermines carriers' revenue; 2) the H-Force increases the cost of FFs but carriers can benefit from it.

4.8 Experiment 4c: If-then Pricing Decision vs. RL Pricing Decision

The aim of this experiment is to compare the learning performance of if then learning and RL learning. An experiment was conducted where the defender adapted its markup by executing one of the four RL models, while the challenger adjusted its pricing decision on an if-then basis. The optimal settings for the learning models are determined as follows. First, the defender executes one of the RL models using the optimal parameter settings determined in Section 4.6.

The challenger does an extensive search to determine the best aggressiveness (ag_i) setting for if-then learning against the defender. Then, given this aggressiveness setting for the challenger, the defender does an extensive search of its parameter setting for the RL model it is using. This procedure is repeated until a Nash equilibrium is reached (shown in Table 4.4): the defender's and challenger's parameter settings are all the best responses to each other, and none of them can do better by unilaterally deviating from the optimal settings.

The performance of the challenger and the defender under such condition is shown in Fig. 4.16. Learning on an if-then basis gives better performance than any of the four RL models. Thus, RL does not always perform well in competition with other FFs.

A possible reason could be that we currently define state in terms of the number of shippers whose cargo was successfully acquired in the latest transaction. We have not yet incorporated other relevant information (for example, previous price level, demand and supply level) to determine the current state. In addition, the action space for RL (markup $\in [0,30\%]$, 31 possible actions) is larger compared with that of the 'if-then' learning (only 3 possible actions). In other words, it takes fewer iterations for the 'if-then' learning to explore the entire action apace to identify a better action for the current state. As a result, the "if-then" learning is more responsive to the changes of its rivals and the environment. If more criteria are incorporated to amplify the number of states and simplify the action space, the performance of RL could be improved significantly.

Table 4.4 Optimal setting for model parameters (If-then vs. RL)

challenger (if-then)	Defender (RL)
$ag_i = 0.70$	Action-value, *ε=0.05*
$ag_i = 0.85$	softmax, $\tau = 500$
$ag_i = 0.80$	SARSA, $\alpha = 1, \gamma = 0.05$
$ag_i = 0.80$	Q-learning, $\alpha = 0.30, \gamma = 0.05$

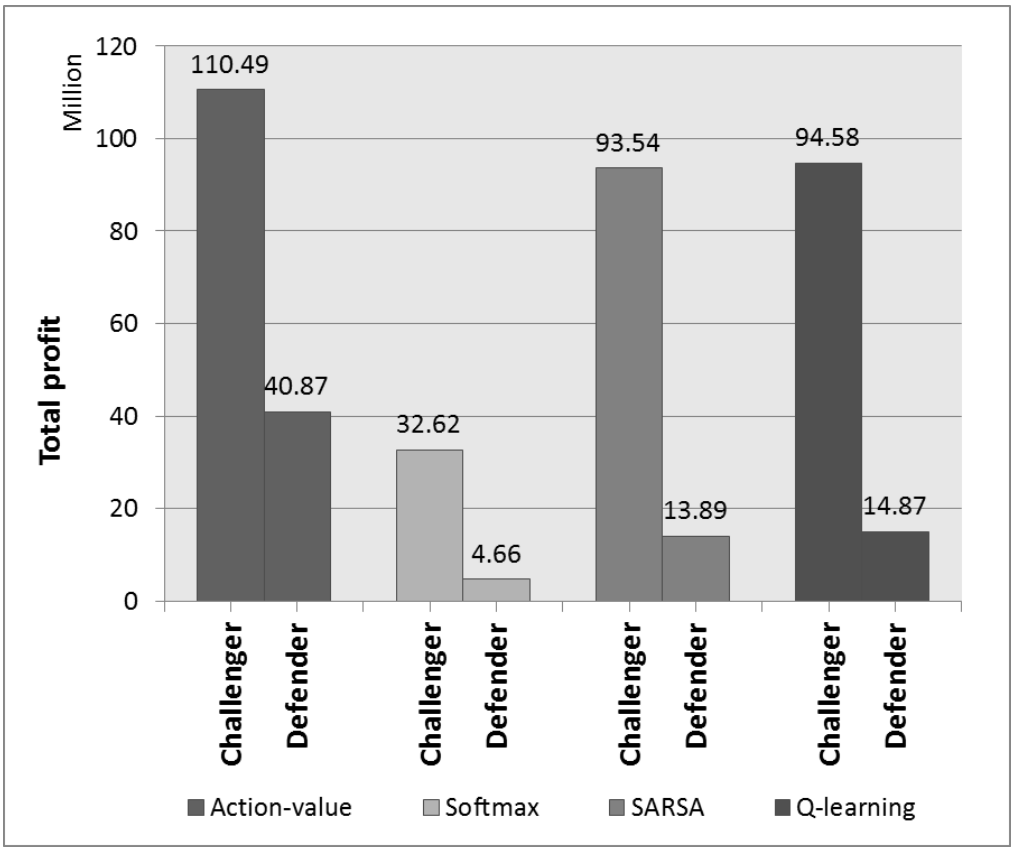

Fig. 4.16 Pricing performance –IT against RL

4.9 Experiment 4d: How Aggressive Should a FF Be on Pricing?

The aim of this experiment is to investigate how aggressive should a FF be in pricing. An experiment was conducted where both challenger and defender learned on an if-then basis. An extensive search was first conducted to find the optimal settings for the parameters associated with both FFs. As both FFs are symmetric in behavior, they are denoted as FF_i and $FF_{\underline{i}}$ respectively.

Fig. 4.17 shows the total profit earned by FF_i and $FF_{\underline{i}}$ given the aggressiveness $ag_{\underline{i}}$ of the other $FF_{\underline{i}}$. For each setting of $ag_{\underline{i}}$ for $FF_{\underline{i}}$, FF_i has an optimal response ($ag_i^*|_{ag_{\underline{i}}}$). When competing with FFs with lower aggressiveness, a FF can be better off by being more aggressive. Moreover, the general level of a FF's profitability is affected by its components' aggressiveness, and this aggressiveness determines the intensity of the competition in the market. More intensive competition will drive down profit for both actors

By plotting the optimal ag_i^* against $ag_{\underline{i}}$, we obtain the frontier depicted in Fig. 4.18. This frontier represents the reaction curve of FF_i given the action taken by $FF_{\underline{i}}$. In order to find the equilibrium aggressiveness of both FFs, we need to find the interaction of the reaction curve of FF_i and $FF_{\underline{i}}$. Due to the symmetric behavior of both FFs, the reaction curve of $FF_{\underline{i}}$ given the action taken by FF_i should be the same as the frontier shown in Fig. 4.18. Thus this curve also yields the equilibrium frontier for both FFs. Each point on the frontier is a Nash Equilibrium because the action of each FF is already the best response to that of the other. By referring to this curve, a FF can figure out its optimal aggressiveness when competing against competitors.

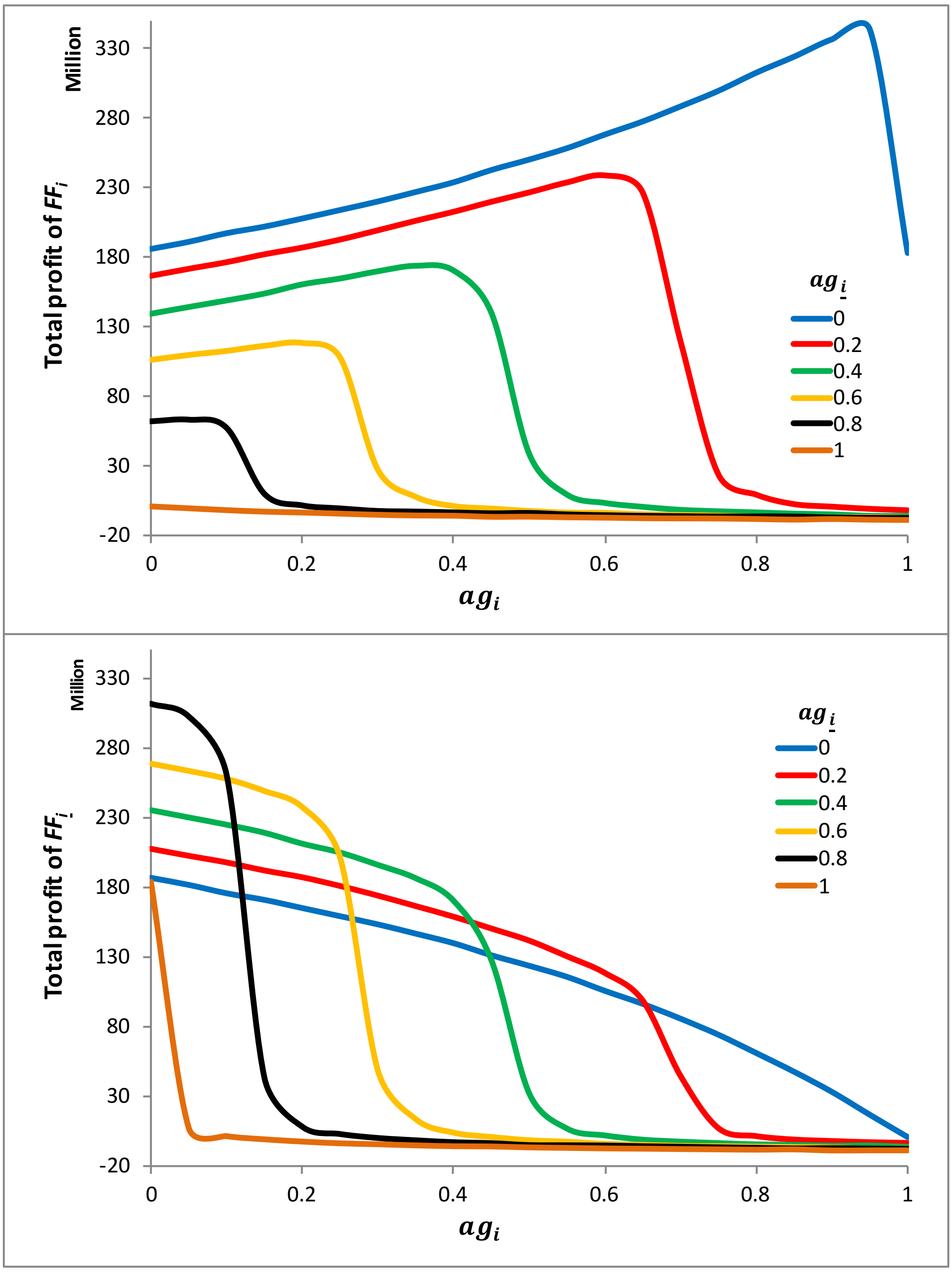

Fig. 4.17 Profits earned by FF_i given the aggressiveness of $FF_{\underline{i}}$

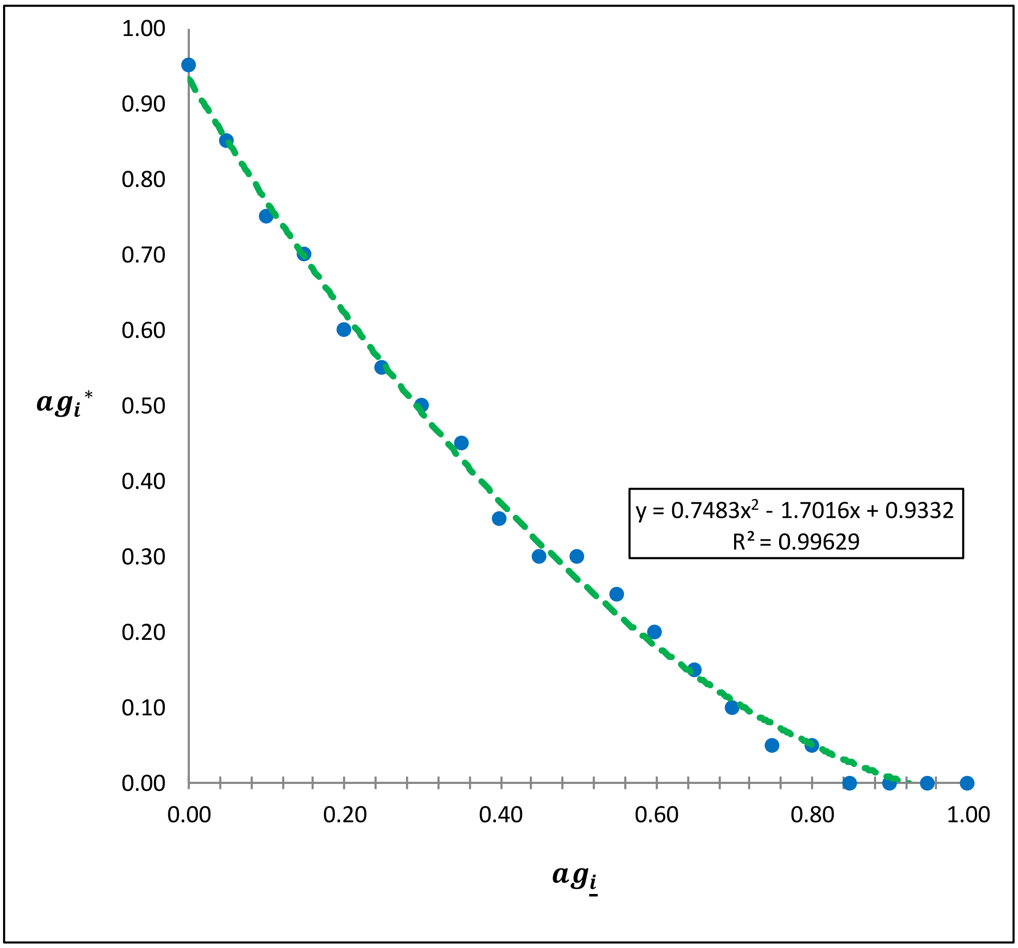

Fig. 4.18 The reaction curve of FF_i

CHAPTER 5 PRICING DECISIONS WITH REAL WORLD ACCESSIBLE INFORMATION

5.1 Introduction

The aim of this chapter is to help a FF make pricing decisions based on the information that is accessible to the FF in the real world operations. This chapter extends the learning approaches discussed in Chapter 4 by applying them in a different pricing situation: FFs are able to learn but only with the information that is available to them in reality.

The information that is available to a FF is shown in Fig. 5.1. The FF knows its own objectives, and can refer to its internal information (profit gain or loss, market share gain or loss, and whether quotations are accepted or not) and external information to update its pricing decisions over time. For the external information, the FF knows:1) number of shippers and each individual shipper's demand of cargo movement; 2) number of carriers. However, the FF does not know carriers' full freight rate scheme and available capacity. Instead, the FF each time announces cargo volume and requirements to carriers after formulating its own cargo split plan. The FF will seek for confirmations from carriers and redo cargo split until all cargo is assigned and transported. The FF has no information on its competing FFs, and knows no more information other than mentioned above.

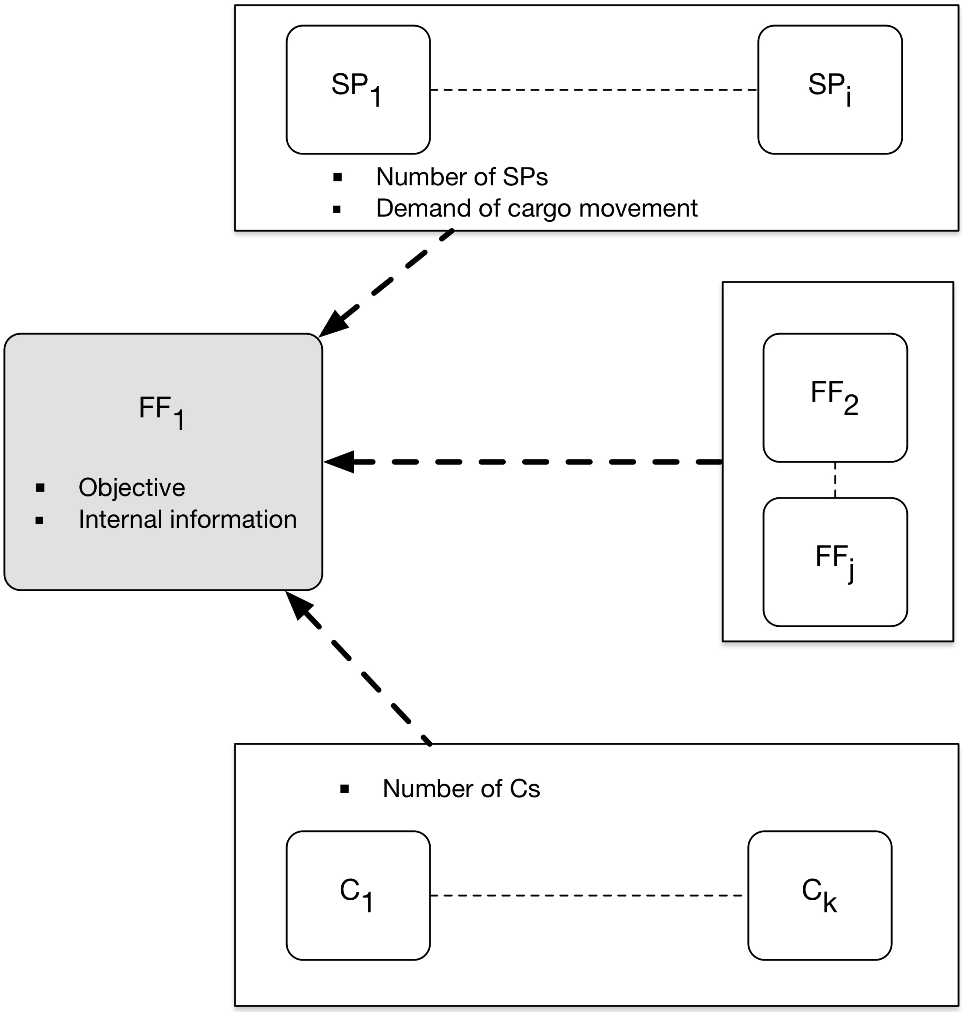

Fig. 5.1 Information that is accessible to a FF in real world operations

In this chapter, the three-tier interaction between shippers, FFs, and carriers is examined when there are multiple players in each tier. Multi-agent simulations are conducted to get deeper insights into a FF's pricing decisions that are not well captured by the approaches proposed in Chapter 3 and Chapter 4 : we examine the scenarios when the demand from shippers and the supply offered by carriers are allowed to fluctuate. Although a FF cannot control the fluctuation of demand and supply, the FF is able to adjust its pricing decisions to react to the fluctuation. In addition, although the market is assumed to be over supply over the long horizon, for a short time there may be insufficient supply. The simulation conducted in this chapter also takes into account undersupply in the market.

The synchronous time model adopted in Chapter 4 (everything happens within a time step n and then the time jumps to the next time step n+1) is also relaxed in this chapter: by assuming asynchronous time model, activity and events can happen at any time point. According to (Borshchev, 2013), asynchronous time assumes that there is no "grid" on time axis and events may occur at arbitrary moments, exactly when they are to occur. In this way, the simulation can be conducted in a more realistic manner.

5.2 Research context

In this chapter, we examine the interaction between shippers, FFs, and carriers with multiple actors in each tier. As shown in Fig. 5.2, how a FF is able to make optimal pricing decisions is investigated in a context comprised of K shippers ($SP_k, k = 1,2, \dots, K$), I freight forwarders ($FF_i, i = 1,2, \dots, I$) and J carriers ($C_j, j = 1,2, \dots, J$). All shippers need to transport cargo between the same origin and destination pair. An individual SP_k needs to transport V_k unit of cargo. There are multiple carriers in the market, and they are available to all FFs.

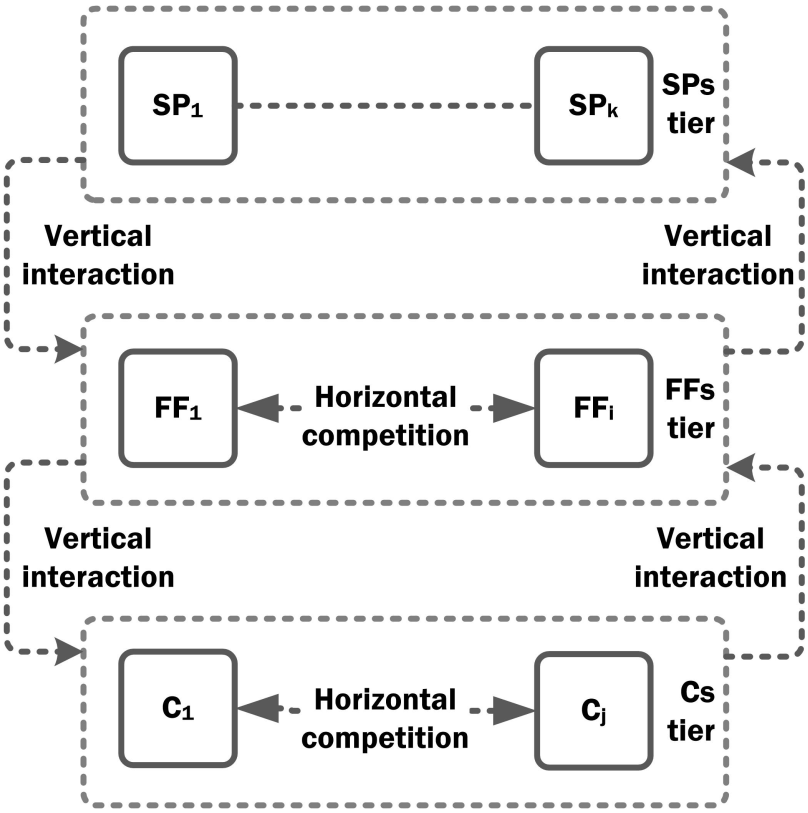

Fig. 5.2 The Three-tier interaction with multiple players in each tier

The demand comes from shippers, which is supposed to be satisfied by the supply offered by carriers. On the supply side, the market is assumed oversupplied: the total supply offered by carriers is greater than the demand for cargo movement. However, for a short period, there can be under supply in the market. We also assume that the demand of cargo movement and the supply offered by carriers may fluctuate. Carriers may adjust their fleet size in response to the changes in demand, but how to adjust fleet size is not the focus of this research. We adopt the above assumptions because the emphasis of the research is on pricing decisions by FFs in a competitive oversupplied market. The aim of this research is to assist a FF to identify a pricing decision via the interaction with other actors, given the demand from shippers and the supply from carriers. The FF assures its own profitability as long as it can beat its competitors.

We would like to assist a given FF (FF_1 in Fig. 5.2) in its pricing decisions via the interaction with other actors. How shippers, FFs, and carriers interact with each other is already presented in Fig. 5.2. From the FF's perspective, it does not know the full information of the entire system. The FF only knows: 1) demand of cargo movement from shippers; 2) whether quotations are accepted or not; 3) number of available carriers in the market; 4) price quoted by carriers and volume of cargo that can be accepted by each carrier after each solicitation; 5) internal information, for example, profit gain or loss, market share improvement or loss etc.

The vertical interaction between shippers and FFs as well as that between FFs and carriers are considered. The first stage of the vertical interaction happens between shippers and FFs. Each shipper can have its own goal, and the goal of different shippers can very from each other. All shippers are outsourcing shippers, and they all independently choose one preferred FF based on proposed charges. The demand of each shipper is allowed to vary. Shippers have no incentive to split their cargo between FFs because outsourcing by shippers is common in the real world operations. Most of the shippers do not want to design and execute their own cargo movement plans. Instead, they prefer to partner third party logistics companies and rid themselves of non-core services and additional functions that are not typical for a company. All FFs are assumed to be NVOCCs, and each FF can have its own goals which may very across different FFs. No FFs have the incentive to cooperate with others; instead, they compete for limited cargo from shippers and available capacity from carriers. Communication and information exchange are not possible between FFs, and they do not form a coalition.

The second stage of the vertical interaction happens between FFs and carriers. Each FF aims at achieving its own goals by splitting cargo among available carriers. Each FF can have its own goals and the objective of different FFs may vary. Each carrier does not reveal its full freight rate scheme and available capacity to FFs. Each time a FF sends a solicitation (including cargo volume, requirements etc.) to a specific carrier, and the carrier only responses unit cargo movement charge and volume of cargo that can be accepted. This procedure repeats until all cargo from the FF is assigned. In the end, carriers transport cargo physically from the origin to the destination. Each carrier is allowed to vary its fleet size and can have its own objective and ways of adjusting freight rate scheme. However, how carriers adjust their pricing schemes and fleet size is not the focus of this research.

Horizontal competitions within tiers are also considered. FFs compete for business from shippers by proposing prices, and compete for the most cost-effective carriers by splitting cargo among carriers. The competition between carriers is taken into account by: 1) carriers' freight rate scheme; 2) how carriers decide which FFs to serve once solicitations from FFs are beyond capacity. The competition between shippers is not considered for now.

This chapter also extends the synchronous time model assumption adopted in Chapter 4 by assuming asynchronous time model. According to (Borshchev, 2013), asynchronous time model assumes that there is no "grid" on time axis and events may occur at arbitrary moments, exactly when they are to occur (Fig. 5.3). However, the study in Chapter 4 assumes synchronous time model during the interaction between shippers, FFs, and carriers (also during multi-agent simulations). Synchronous time assumes that things can only happen during discrete time steps (they are "snapped to the time grid"), and nothing happens in-between. With the synchronous time model assumption, each player performs all its actions or do nothing at time n and then the time jump to time $n + 1$ (Fig. 5.4): both shippers announce volume of cargo to FFs, and both FFs make pricing decisions simultaneously and then response quotation. All the activities mentioned above occur within one time step, and then the time jumps to the next time step.

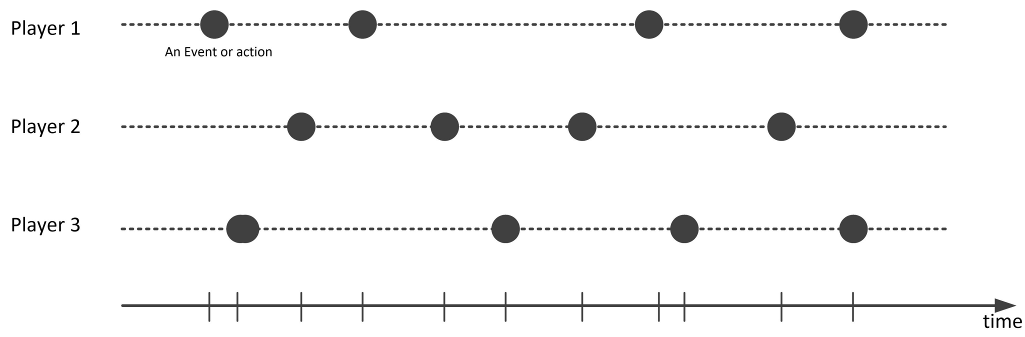

Fig. 5.3 Asynchronous time model

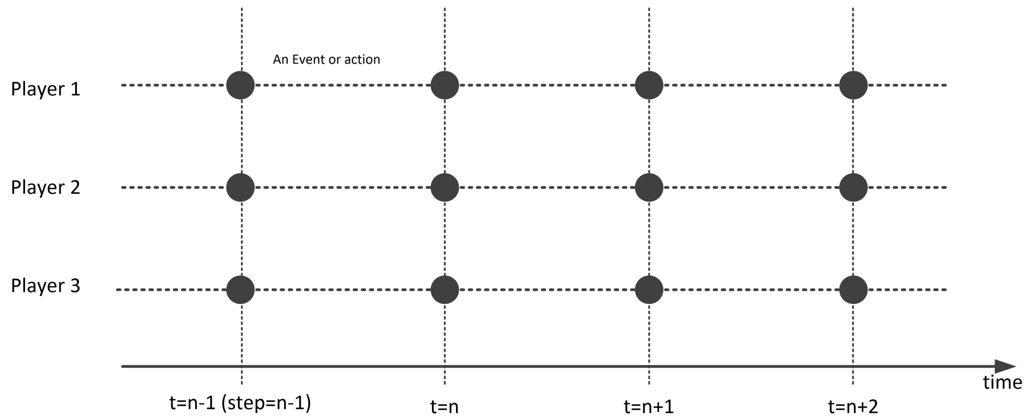

Fig. 5.4 Synchronous time model

5.3 Decision Making Model for Each Party

In reality, each actor can have its own objectives and decision making models. This section presents how the behavior and decision making models of one actor vary from those of another. How information is exchanged between different actors will be discussed from the perspective of a specific shipper (Section 5.3.1), FF (Section 5.3.2), and carrier (Section 5.3.3).

5.3.1 Shippers

From a specific shipper's perspective (SP_k), the information flow between the shipper and its integrating FFs is presented in Fig. 5.5. The shipper first announces cargo volume and requirements to each FF in the market. Each FF then responds its quotation back to the shipper. This shipper will compare all received quotations and then select a preferred FF.

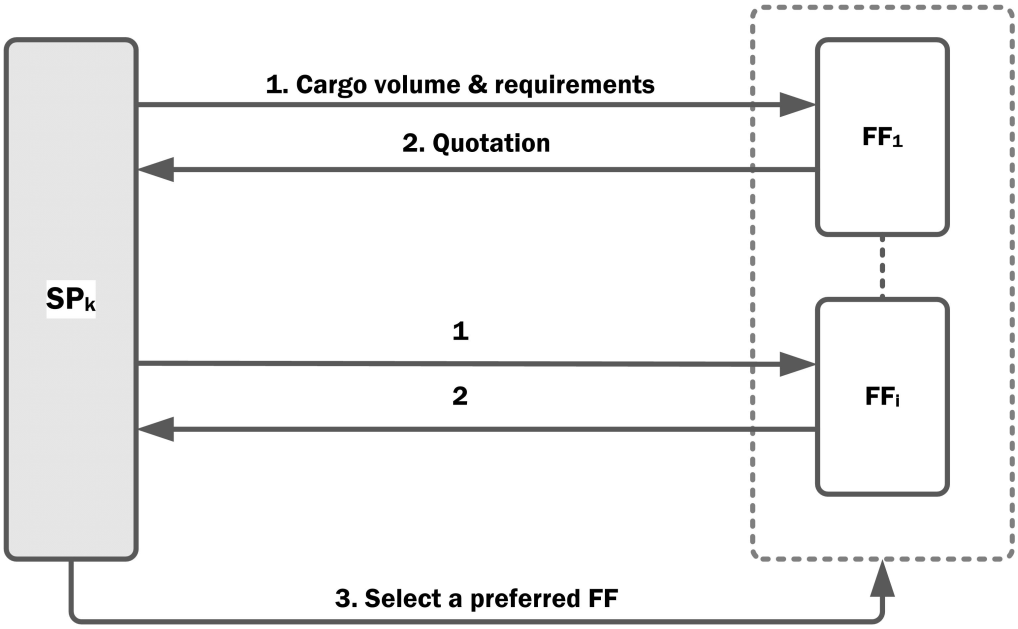

Fig. 5.5 The information flow between a specific shipper and its interacting FFs

In order to take into account variations in shippers' decision making procedure, a specific shipper's selection behavior for the preferred FF is modeled in three ways (shown in Table 5.1):

A type A shipper does not choose the FF who quotes the highest or the lowest price. Instead, the shipper randomly chooses one FF among all the other FFs. In reality, when some shippers make decisions, their rationality is limited by the availability of information, the tractability of the decision problem, the cognitive limitations of their minds, and the time available to make the decision. They may just seek a satisfactory solution rather than an optimal one.

A type B shipper always chooses the FF who quotes the lowest price. In reality, some shippers are quite sensitive about shipping cost. They are willing to switch to a new service provider as long as a lower price can be achieved. For example, when shippers transport less time sensitive cargo, they are willing to pay less attention on level of service as long as cargo can be transported from the origin to the destination with the lowest shipping cost.

The objective of a type C shipper is to maximize its utility. When the shipper wants to transport cargo from an origin to a destination, there are multiple factors affecting its decision. This shipper's perception and preference on various FFs can be measured by its utility function. The alternative that brings the highest utility will be selected. For example, we used multi-nominal logit model to model the selection behavior of shippers in Section 3.3.2.2.

Table 5.1 Variations in shippers' selection behavior

Type	Selection behavior of preferred FF
A	Bounded rationality
B	Always choose the FF who offers the lowest price
C	Modeled by the multi-nominal logit model (discussed in Section 3.3.2.2)

5.3.2 FFs

FFs are an intermediary party who facilitates the transactions between shippers and carriers in the logistics chain. From a specific FF's perspective (FF_i), the information flow between the FF and its integrating shippers is presented Fig. 5.6. Various shippers first announce volume of cargo and requirements to the FF. By consolidating the cargo from all shippers, the FF announces consolidated cargo volume and requirements to each available carrier in the market. Each carrier then responds unit cargo price and volume of cargo that can be accepted. The FF has no information on how each carrier decides quoted price and volume of cargo that can be accepted. Based on the above information, the FF makes its pricing decision and responds unit cargo price back to each shipper. In the end, each shipper decides whether to accept the quotation or not. If a quotation is accepted, the shipper will offer all its cargo to the FF.

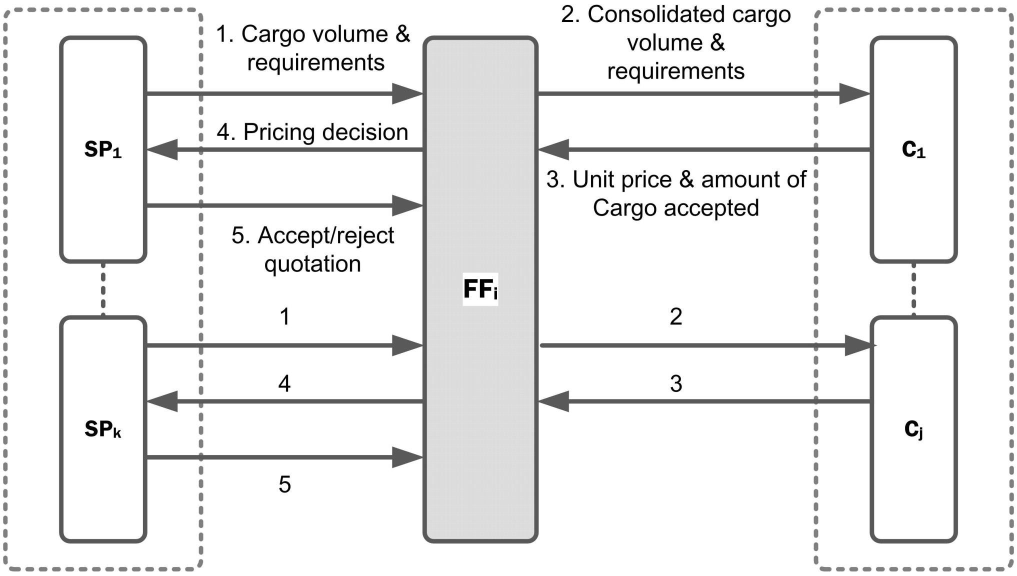

Fig. 5.6 The information flow between a specific FF and its interacting shippers

Similarly, from the FF's perspective (FF_i), the information flow between the FF and its integrating carriers is presented Fig. 5.7. After receiving cargo from various shippers, the FF needs to further split cargo among available carriers so that all the cargo received can be transported from the origin to the destination. Once there is remaining cargo to be transported, a FF first announces volume of cargo and requirements to all available carriers. Each carrier then responds quotation and volume of cargo that can be accepted. After comparing all quotations and accepted cargo volume from various carriers, the FF decides which carrier to choose. The above procedure repeats until all remaining cargo is transported.

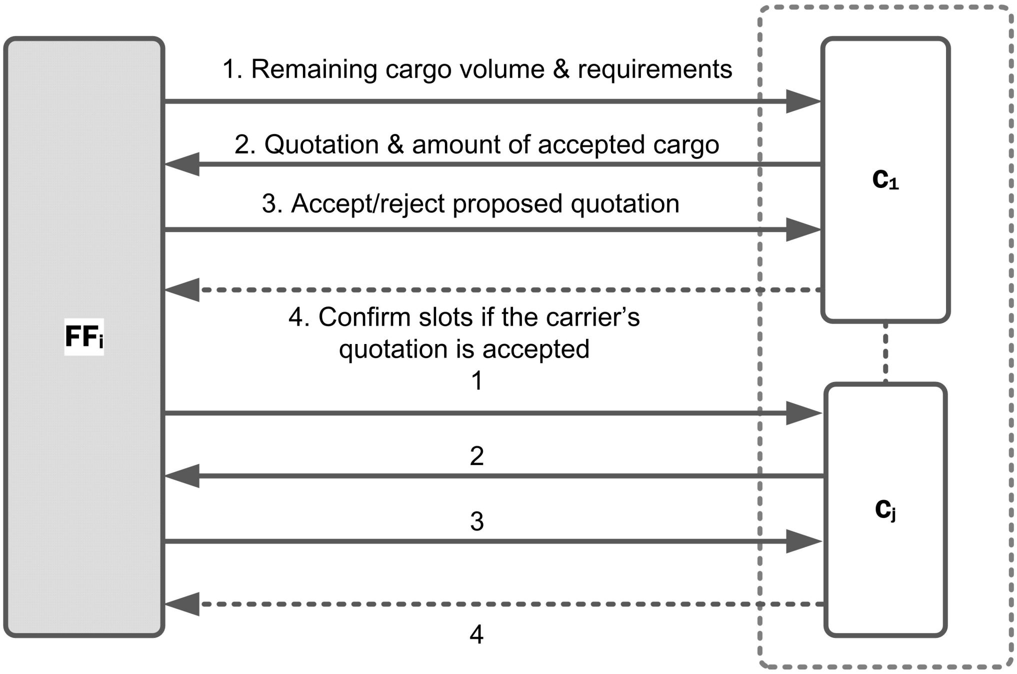

Fig. 5.7 The information flow between a specific FF and its interacting carriers

In order to take into account variations in FFs' behavior and decision making models, three types of FFs are considered (shown in Table 5.2).

A type A FF applies fixed markup and reviews the markup periodically. When contacted by a shipper for cargo movement service, the FF first estimates potential cost and then responds a quotation by adding in its desired markup. The desired markup can be formulated based on the FF's experience, objectives, or other analytical analysis approaches (for example, the game theoretical approach proposed in Chapter 3). The markup is reviewed periodically by examining the FF's pricing performance in previous transactions. If a high level of profit or market share was achieved, this FF will have incentives to increase its markup for future transactions. Otherwise, lower markup will be preferred.

In reality, most FFs behave in this way because they are the intermediary party who earns price difference between the revenue gained from shippers and the fees paid to carriers. The simplest way of making pricing decision is to add a markup to costs so that a certain level of profitability can be achieved.

A type B FF learns by one of the four RL models proposed in Section 4.3.1. The FF is able to learn by trial and error so that no training data is required. RL learning is easy to implement by only using the information that is available to FFs.

A type C FF learns on if-then basis as presented in Section 4.3.2. This is also an intuitive way of learning by trial and error.

Table 5.2 Variations in FFs' pricing model

Type	Description
A	Apply a fixed markup and review the markup periodically
B	Learn the optimal pricing decision by applying one of the four RL models proposed in Section 4.3.1. • B1: Action value • B2: Softmax • B3: Sarsa • B4: Q-learning
C	Learn on if then basis as presented in Section 4.3.2.

In order to incorporate more criteria to amplify the number of states and simplify the action space so as to improve the learning efficiency of RL models, in this chapter the sate of a FF is defined in a two dimensional manner (as shown in Fig. 5.8): pricing performance (market share) and markup level. From a given FF's perspective, a state is defined with respect to its latest markup level and latest market share. The markup of the FF can be at a high level, a medium level, or a low level (Fig. 5.9). Within each markup range (for example, high markup range), the number of possible markup points is assume to be mp_i. It means the entire action space of the FF is divided evenly into ($3mp_i$ - 1) segments and the boundary of each segment is a possible markup point for the FF. The market share associated with a FF can be estimated as the portion or percentage of cargo that obtained by the FF with respect to all the cargo requested by shippers (Fig. 5.10). It can be calculated as the volume of cargo obtained by the FF divided by the total volume of cargo requested by all shippers.

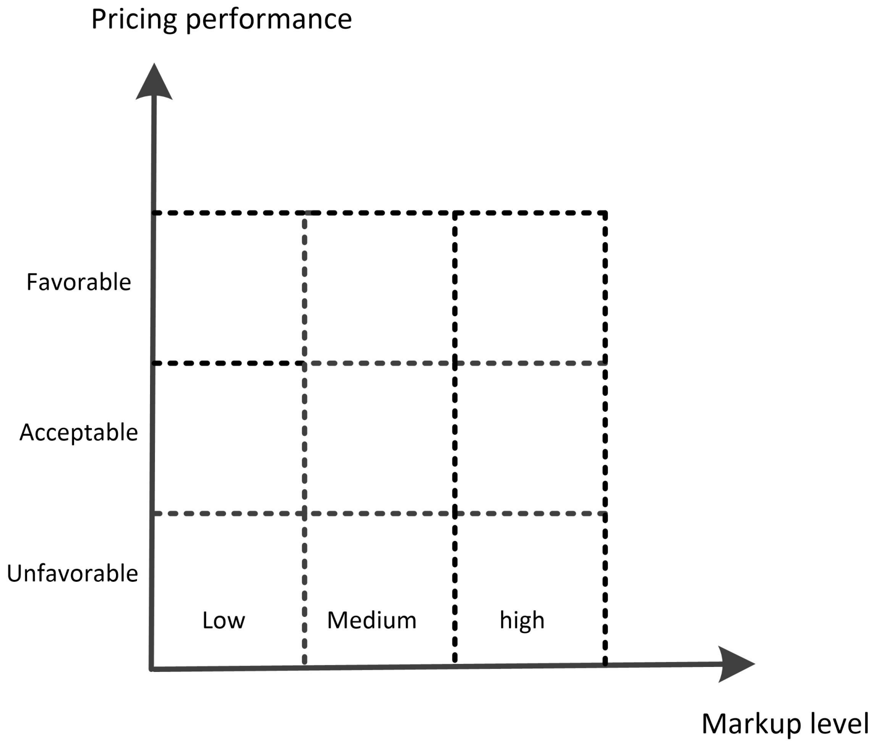

Fig. 5.8 States of a FF

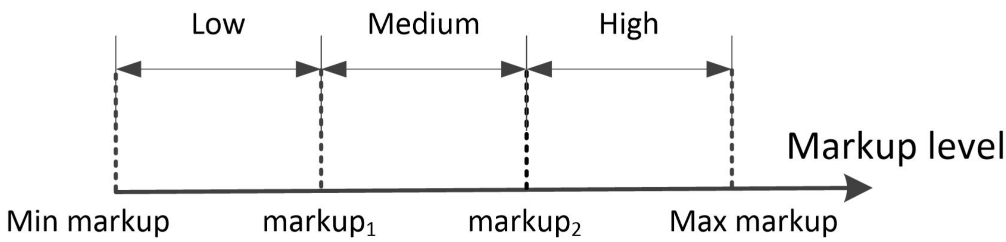

Fig. 5.9 Markup levels of a FF

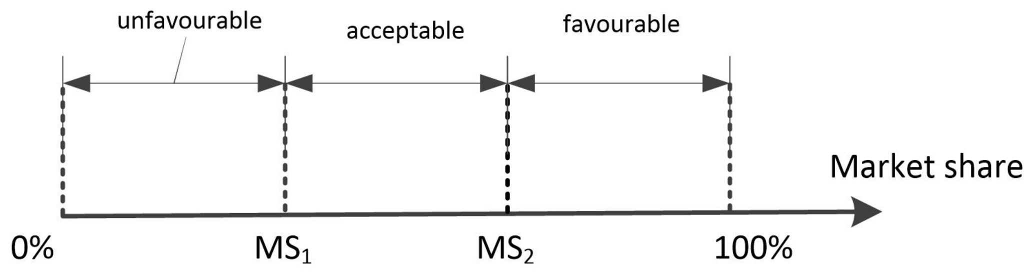

Fig. 5.10 Define pricing performance of a FF

In this chapter, as the demand and supply are allowed to vary, the best pricing decision for a FF may not be the one that brings the highest total profits. Higher total profit may be due to higher total demand in the market (for example, peak season for cargo movement, like Christmas). Thus, we define the reward of FF_i as shown in Equation (5.1): the reward of FF_i is measured by the amount of profits gained divided by the highest possible total profit the FF is able to earn in the market. PD_i is the price decision made by FF_i; $cost_i^{actual}$ is the actual cost of FF_i after taking action PD_i. TV_i^{actual} is the actual volume of cargo obtained by FF_i. $price_i^{max}$ is the highest possible price for FF_i when quoting price to shippers. CUC_i is the lowest unit cargo cost for FF_i. $\sum_k V_k$ is the total demand for cargo movement from all shippers.

$$r = \frac{\left(PD_i - cost_i^{actual}\right)TV_i^{actual}}{(price_i^{max} - CUC_i)\sum_k V_k} \tag{5.1}$$

5.3.3 Carriers

From a specific carrier's perspective (C_j), the information flow between the carrier and its integrating FFs is presented in Fig. 5.11. Each FF first announces cargo volume and requirements to the carrier. The carrier responds price and volume of cargo that can be accepted to each FF. Each FF compares the quotations from various carriers, and decides whether accept the carrier's quotation or not. In the end, the carrier confirms the FFs to serve.

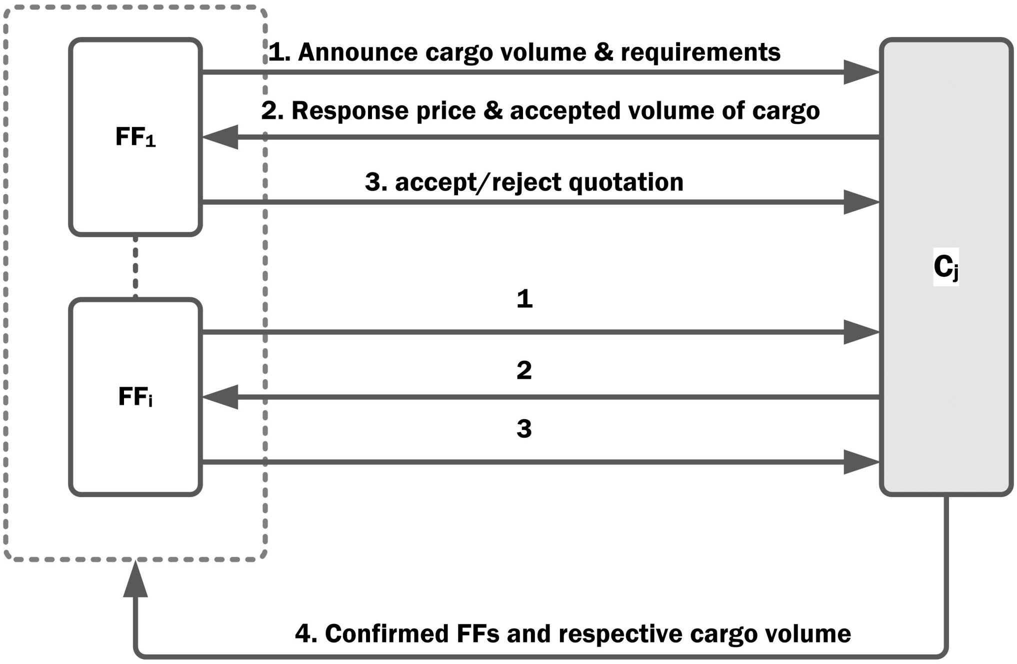

Fig. 5.11 The information flow between a specific carrier and its interacting FFs

In reality, each carrier has its own ways of formulating freight rate scheme as well as deciding which FFs to serve when the solicitations received are beyond the carrier's capacity. As the focus of this research is on the pricing decisions by FFs, we assume that carriers are able to adjust their freight rate scheme but what is the optimal way to do it is not the focus of this study. In order to take into account the variations in carriers' behavior and decision making models, we assume that each carrier has its own way of freight rate scheme formulation and fleet size adjustment.

Carriers offer quantity discount to a FF if the FF offers a cargo volume that exceeds a certain minimum level. Quantity discount is often used by marketers to stimulate higher purchase level. The rational for using quantity discount often rests in the cost of product shipment: shipping costs tend to decrease per item shipped. Fig. 5.12 presents an example of a carrier's freight rate scheme when the carrier offers quantity discount (Type A carrier). A carrier's freight rate scheme may comprise of multiple break points (Fig. 5.12): If cargo volume is less than $Volume_1$, $Price_1$will apply. Similarly, if cargo volume is greater than $Volume_1$, $Price_2$ will apply. This carrier can serve up to the volume of its capacity. Alternatively, a carrier can offer quantity discount in another form (as shown in Fig. 5.13, Type B shipper).

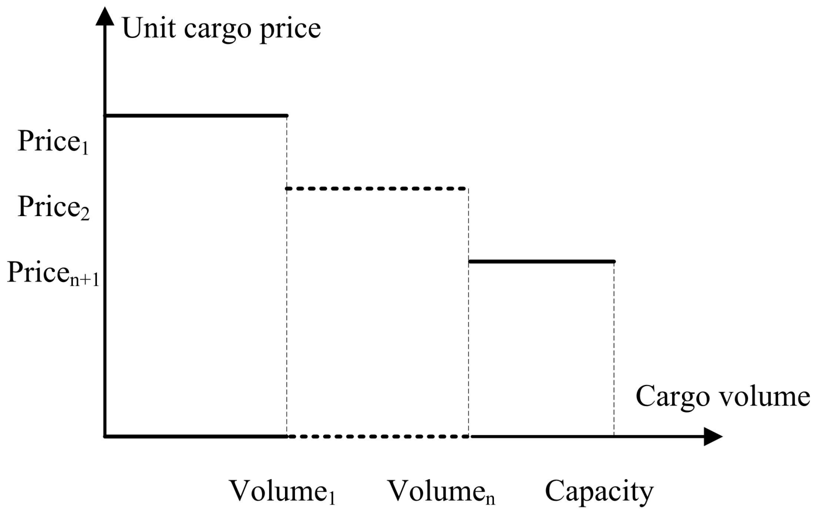

Fig. 5.12 A carrier's freight rate scheme with quantity discount (Type A)

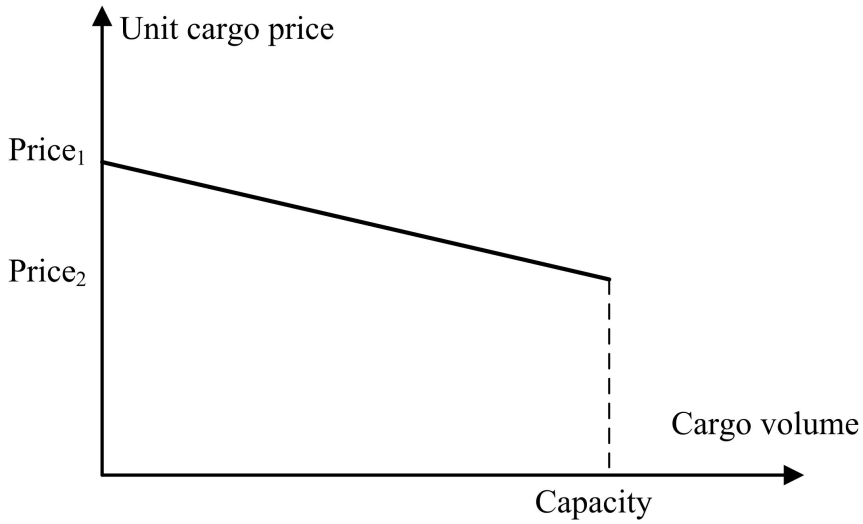

Fig. 5.13 A carrier's freight rate scheme with quantity discount (Type B)

Although there is oversupply in the market, it is possible for a specific carrier to receive multiple solicitations from different FFs. If the total requested demand is beyond the capacity of the carrier, the carrier may prefer the FF who offers larger volume of cargo (Type C) or the one who offers higher prices (Type D).

5.4 MAS Simulation and Experiments

5.4.1 Experiment Setting and Assumption

The simulations conducted in this chapter investigates scenarios when there are multiple shippers, multiple FFs, and multiple carriers in the market. Multi-agent simulations are conducted based on the following case: three shippers want to transport containers from city A to city B. Each shipper is going to outsource its vehicle movement tasks to a FF. There are multiple FFs in the market, and they are available to all shippers. Four vessels (carriers) serve the route from city A to city B, and all FFs are going to make use of these four carriers to design their cargo transportation plans. The information that is accessible to a specific FF has been discussed in Fig. 5.1. All the other features of the three-tier interaction has been discussed in Fig. 5.2.

Four sets of experiments are conducted in this chapter: Experiment 5a, 5b, 5c, and 5d. The first two sets of experiments (Section 5.4.2) are conducted under the synchronous time model assumption. Expt. 5a (Section 5.4.2.1) examines the three-tier interaction under the synchronous time model assumption with three shippers, two FFs, and four carriers in the market. The experiment extends the simulations conducted in Chapter 4 by including more actors in in the market. The demand and supply are assumed to be fixed throughout the entire simulation horizon. Expt. 5b (Section 5.4.2.2) extends Expt. 5a by relaxing the fixed demand and supply assumption. Instead, the demand and supply are allowed to vary. The latter two sets of experiments (Section 5.4.3) are conducted under the asynchronous time model assumption. Expt. 5c (Section 5.4.3.1) extends Expt. 5b by assuming asynchronous time model. Events and activities can occur at any time point. Expt. 5d (Section 5.4.3.2) extends experiment 5c by including five FFs in the market (adding three more FFs into the market).

5.4.2 Synchronous Time Model

With the synchronous time model assumption, the whole analysis horizon is divided into N discrete iterations. Within a specific iteration n (also called time n), all shippers assign cargo among FFs, and all FFs assign cargo among carriers. In the end, all the cargo is transported to the destination and the time jumps to $n + 1$. The above process repeats until the final time N is reached.

5.4.2.1 Experiment 5a: fixed demand and supply with two FFs

In this experiment, the aim is to investigate the performance of RL models when there are multiple shippers and carriers in the market. Whether learning performance of RL models can be improved by redefining state and action space is also the research question this experiment would like to answer. We extend the experiment conducted in Section 4.8 (Expt. 4c) by adding one more shipper and two more carriers into the market. The investigation then focuses on the interaction between three shippers ($SP_k, k = 1,2,3$), two FFs ($FF_i, i = 1,2$), and four carriers ($C_j, j = 1,2,3,4$). How experiments are conducted in this section remains unchanged as we did in Expt. 4c (Section 4.8) other than the following changes:

Settings for the three shippers are presented in Table 5.3. Each shipper has its own demand of cargo movement and selection behavior for the preferred FF. The demand from each shipper is assumed to be fixed throughout the entire simulation horizon.

Table 5.3 Settings for shipper agents (Expt. 5a)

Shipper	Type	Demand	Specifications
SP_1	B	255 TEUs	
SP_2	C	200 TEUs	Price sensitivity =0.06;
SP_3	B	225 TEUs	

1) Type A: do not choose the FF who offers the highest or the lowest price; instead, randomly choose one FF among all the other FFs;
2) Type B: prefer the FF who offers the lowest price
3) Type C: modeled by the multi-nominal logit model (discussed in Section 3.3.2.2)

Settings for the four carriers are presented in Table 5.4. Two of the carriers use liner freight rate scheme and the other two carriers use stepwise freight rate scheme. The supply offered by each carrier is assumed to be fixed throughout the entire simulation horizon.

Table 5.4 Settings for carrier agents (Expt. 5a)

Carrier	Type	Parameters
C_1	A+C	$y = 800 - 0.5x;\ capacity = 300\ TEUs$
C_2	A+D	$y = 600 - 0.3x;\ capacity = 290\ TEUs$
C_3	B+C	$price_1 = 750; price_2 = 600; V_1 = 125;$ $capacity = 310\ TEUs$
C_4	B+D	$price_1 = 700; price_2 = 650; V_1 = 150;$ $capacity = 320\ TEUs$

1) Type A: linear pricing scheme
2) Type B: step-wise pricing scheme
3) Type C: prefer FFs who offer larger volume of cargo
4) Type D: prefer FFs who offer higher price

Settings for the two FFs are presented in Table 5.5. Both FFs are able to learn: FF_1 learns by Q-learning and FF_2 learns on if then basis. How the action space, possible markup points, and state (only for the FF who learns by reinforcement learning) are defined for both FFs is shown in Table 5.5.

Table 5.5 Settings for FF agents (Expt. 5a)

FF	Type	Specifications
FF_1	B4: Q learning	$min\, markup = 0\%; max\, markup = 300\%;$ $markup_1 = 100\%;\ markup_2 = 200\%;$ $MS_1 = 33\%;\ MS_2 = 66\%;$ $mp = 3$ (9 possible markup points)
FF_2	C: If-then basis	$min\, markup = 0\%; max\, markup = 300\%;$ 9 possible markup points (same as FF_1)

B4: Q learning
C: Learn on if then basis presented in Section 4.3.2.

An extensive search was conducted to find the optimal setting for the parameters associated with each FF's learning model. For each combination of setting for parameters, the experiment is run for 20 runs and each run lasts for 500 simulation time. The best setting for the learning parameters associated with FF_1 and FF_2 is presented in Table 5.6. The pricing performance (averaged over 20 runs of 500 simulation time each) of FF_1 and FF_2 under the best setting of learning parameters is presented in Fig. 5.14 (total profit) and Fig. 5.15 (total volume of cargo obtained). By conducting statistical analysis, 20 simulation runs are sufficient and we can conclude that:

First of all, a FF who learns by reinforcement learning can improve its pricing performance by properly defining its states and action space. We proposed in Section 4.8 to incorporate more criteria to amplify the number of states and to simplify the action space to improve the pricing performance of RL learning models. In this chapter, we simplify the action space by using less possible markups points and amplify the number of states by defining the state with respect to latest pricing performance and latest markup level. In this way, the learning performance of RL models improves significantly (FF_1 beats FF_2 in terms of total profits and volume of cargo obtained).

In addition, although the total profit gained by a FF may vary due to variations in the total number of shippers/carriers and their specifications, whether a FF is able to achieve its optimal pricing performance is determined by its capability to beat competitors via learning. No matter how the market condition is, a FF can always assure its profitability as long as efficient learning is possible. Compared with Expt. 4c (Section 4.8), although the number and settings for shippers/carriers are changed in this experiment, the best setting for learning parameters associated with both FFs remains unchanged. As FFs are the middle men between shippers and carriers in the logistics market, it may not be easy for a FF to influence the general level of demand/supply in the market and the behavior of interacting shippers/carriers. However, a FF can adapt its decision and react to the changes of the market. In this way, better pricing performance can be achieved.

Furthermore, the total profit earned by each FF is a result of balancing revenue, cost, and volume. We examine a specific simulation run under the best setting for learning model parameters. The total profit (Fig. 5.18) earned by a

FF is the difference between its total revenue (Fig. 5.16) and total cost (Fig. 5.17). On the one hand, although the total profit earned by FF_1 is higher than that earned by FF_2 throughout the entire simulation horizon (Fig. 5.18), FF_1 does not beat FF_2 in terms of average unit cargo revenue (Fig. 5.21) and average unit cargo profit (Fig. 5.22). On the other hand, although the average unit cargo cost for both FFs are around the same level (Fig. 5.17), FF_1 beats FF_2 in terms of volume (Fig. 5.19)) and market share (Fig. 5.20). As a result, the combination effect of unit cargo revenue (price), volume and unit cargo cost makes FF_1 earn more profit than FF_2.

Table 5.6 Test setting for FFs' learning model parameters (Expt. 5a)

FF	Type	Specifications
FF_1	B4: Q learning	$\alpha = 0.30, \gamma = 0.05$
FF_2	C: If-then basis	$ag_i = 0.80$

B4: Q learning
C: Learn on if then basis presented in Section 4.3.2.

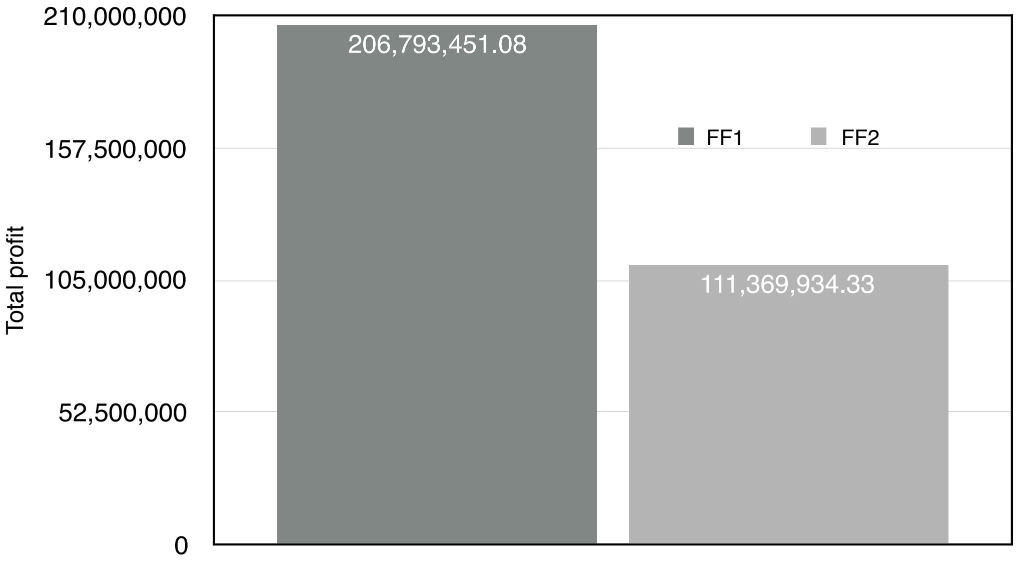

Fig. 5.14 Pricing performance of FF_1 and FF_2 –total profit earned

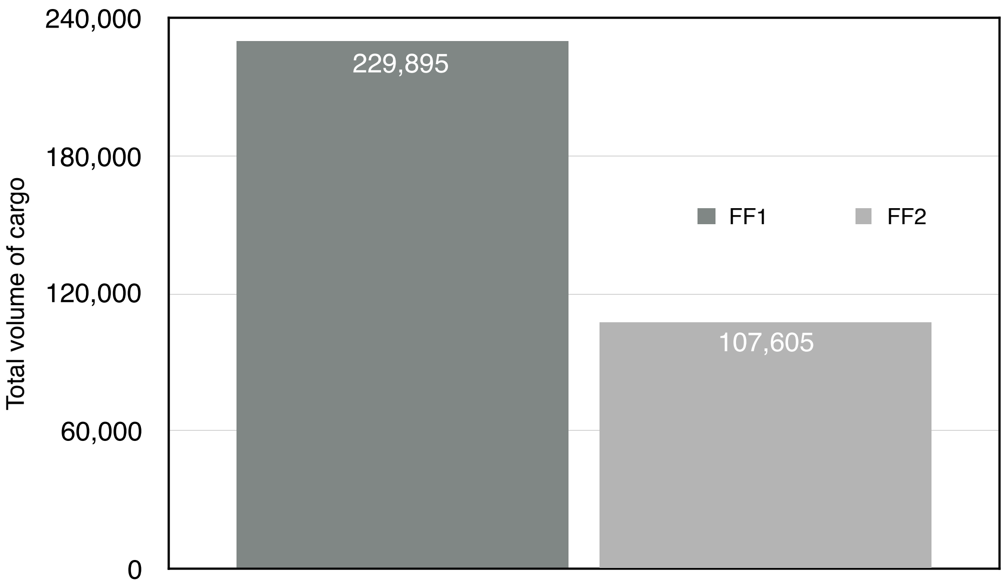

Fig. 5.15 Pricing performance of FF_1 and FF_2 – volume of cargo obtained

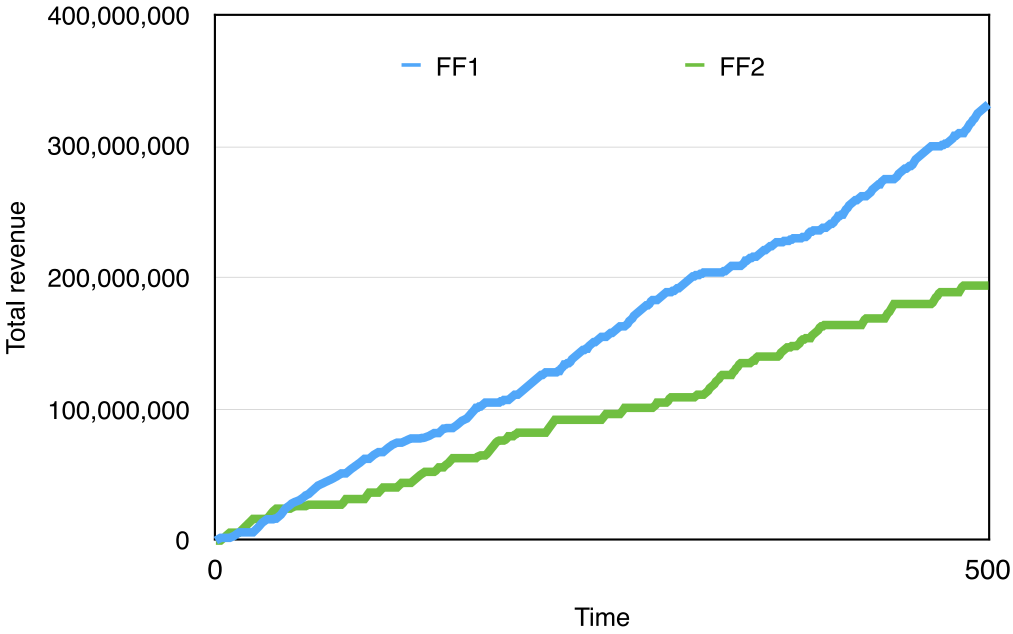

Fig. 5.16 Total revenue earned by FF_1 and FF_2

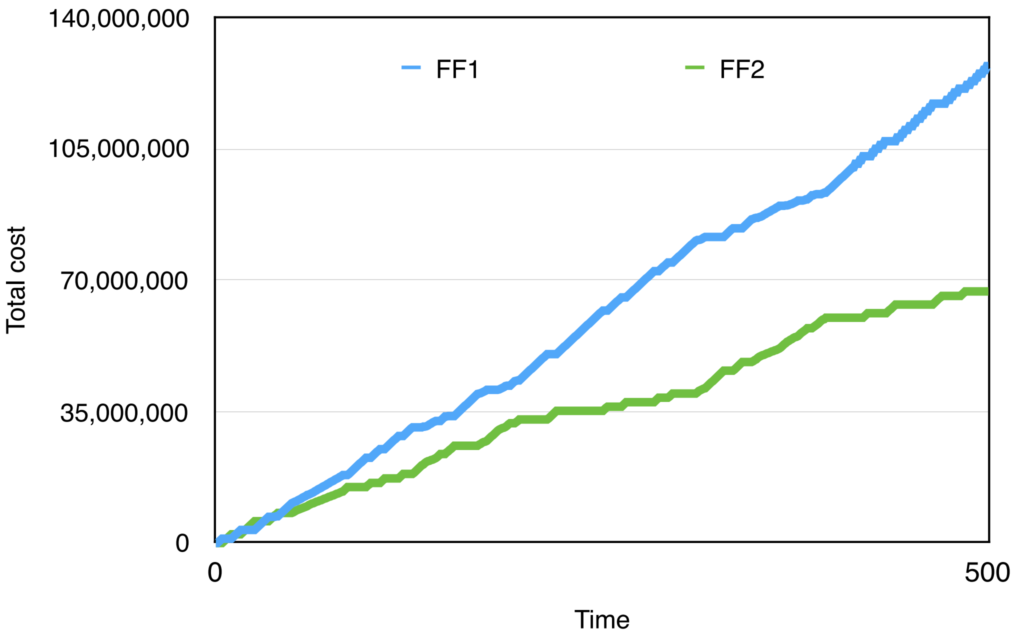

Fig. 5.17 Total cost of FF_1 and FF_2

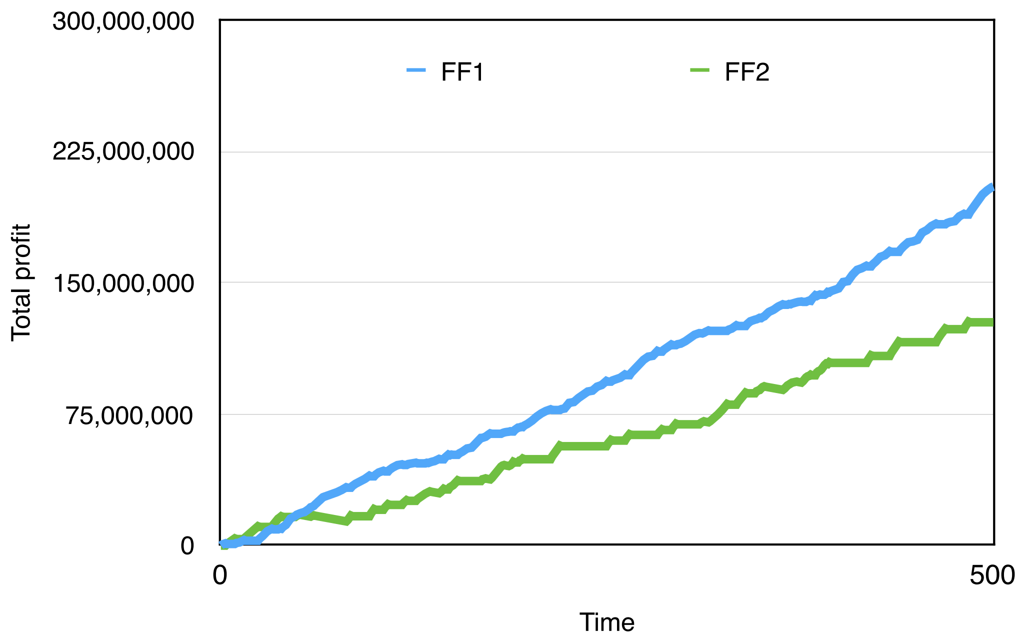

Fig. 5.18 Total profit earned by FF_1 and FF_2

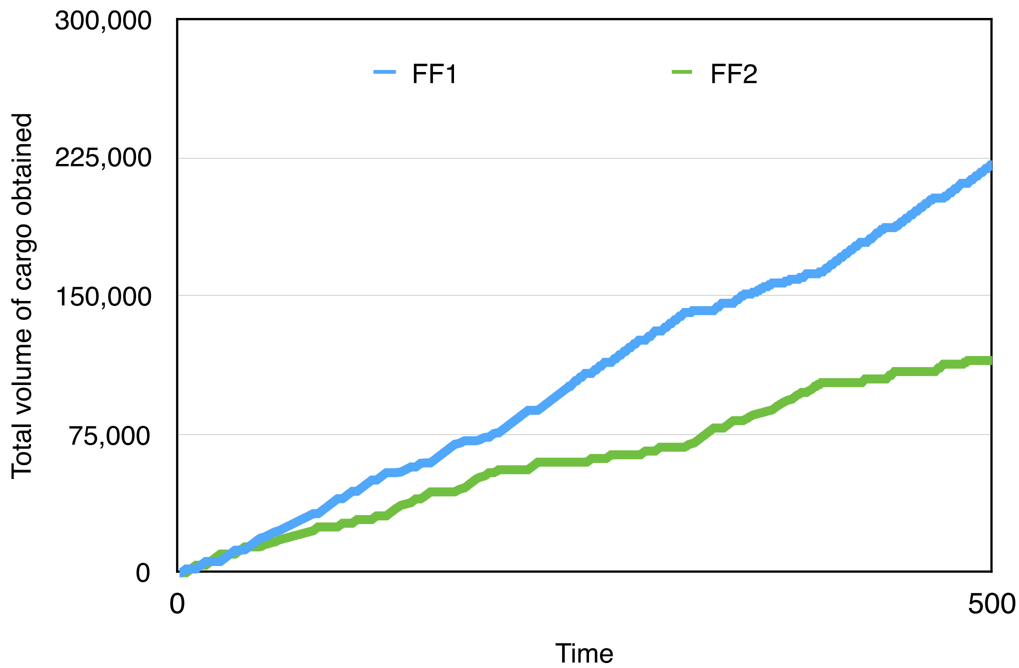

Fig. 5.19 Total volume of cargo earned by FF_1 and FF_2

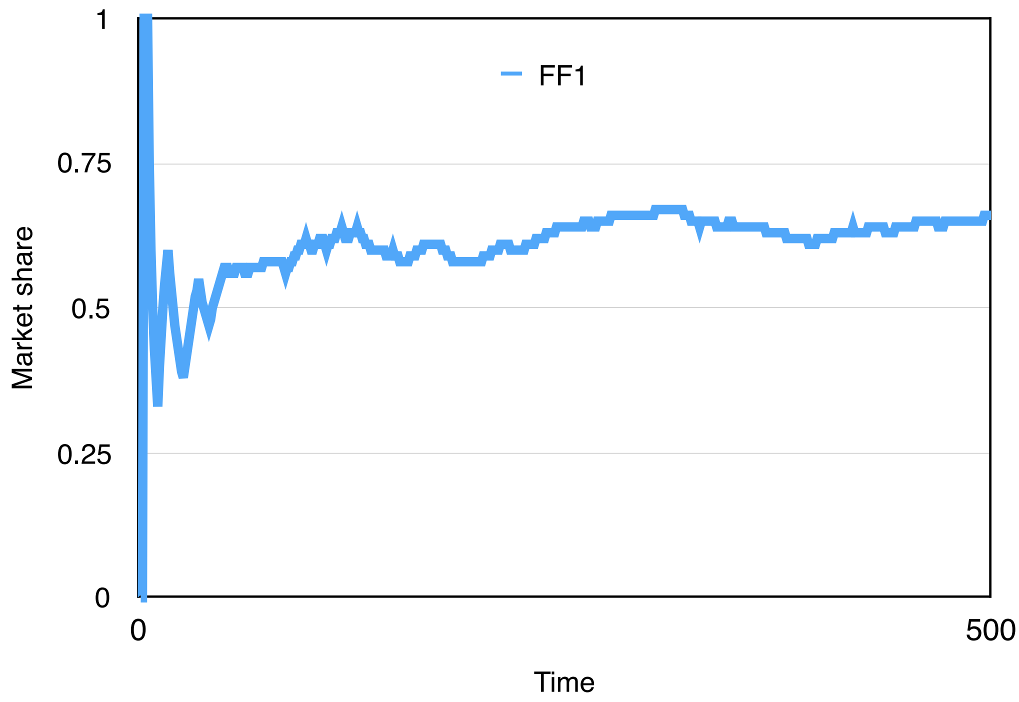

Fig. 5.20 Market share of FF_1

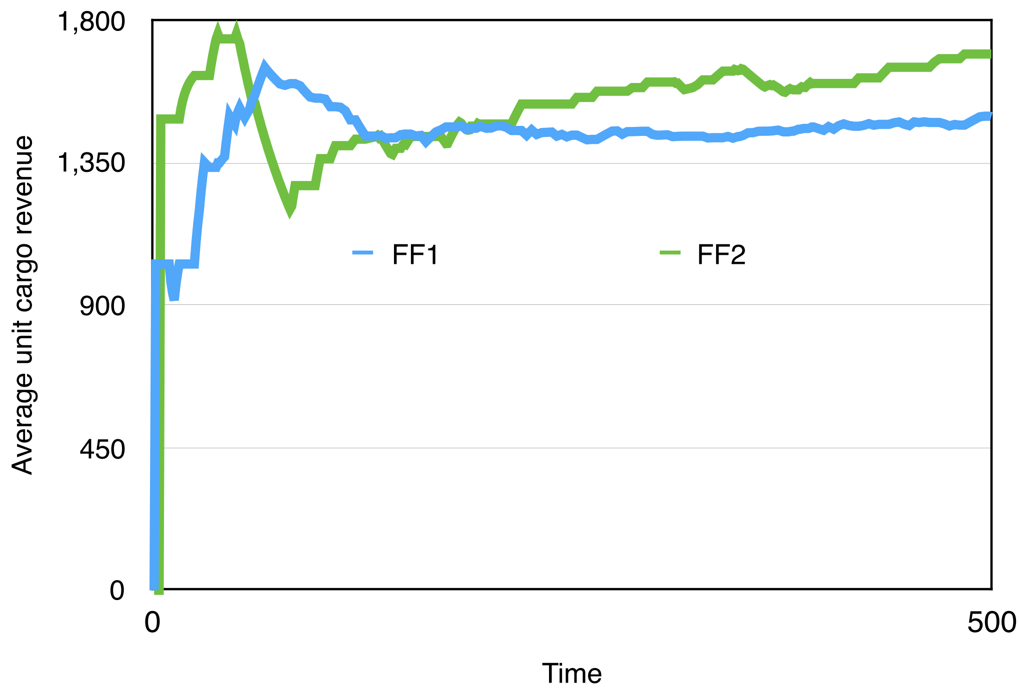

Fig. 5.21 Average unit cargo revenue of FF_1 and FF_2

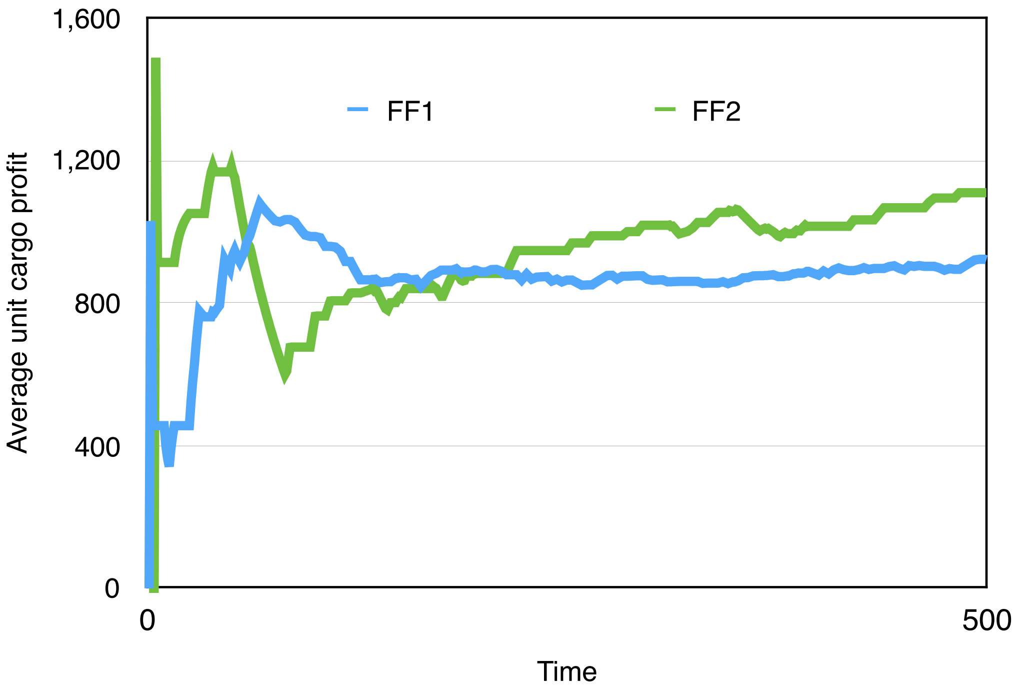

Fig. 5.22 Average unit cargo profit of FF_1 and FF_2

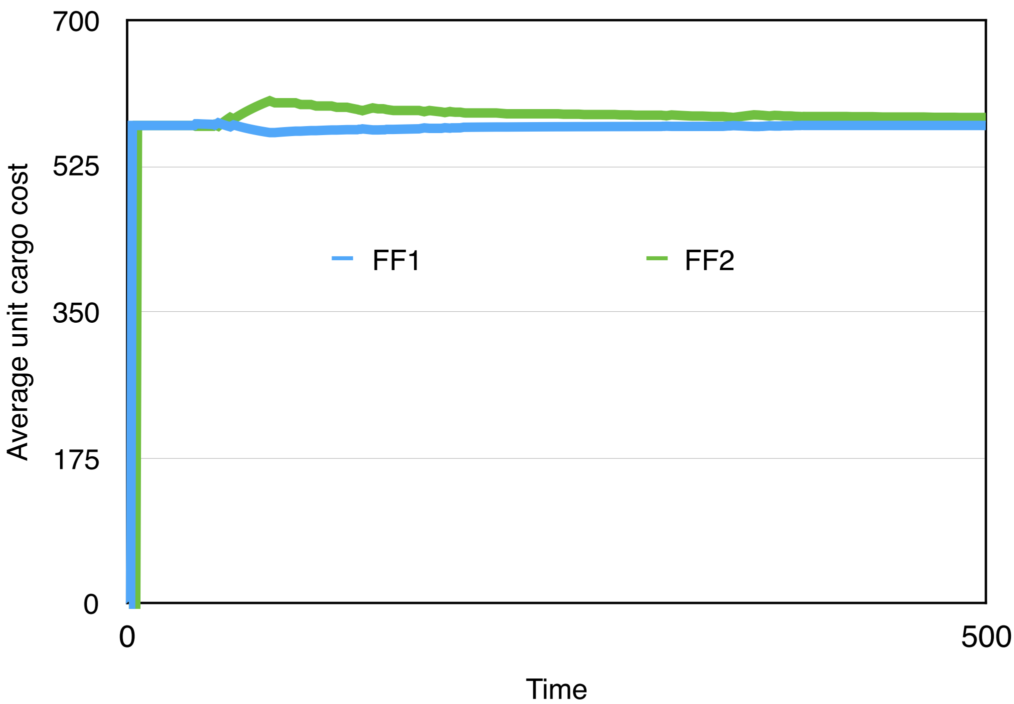

Fig. 5.23 Average unit cargo cost of FF_1 and FF_2

5.4.2.2 Experiment 5b: flexible demand and supply with two FFs

In this experiment, the aim is to investigate the performance of RL models when demand and supply in the market are allowed to vary. We extend Expt. 5a by relaxing the fixed demand and supply assumption. The investigation is still on the interaction between three shippers ($SP_k, k = 1,2,3$), two FFs ($FF_i, i = 1,2$), and four carriers ($C_j, j = 1,2,3,4$), but demand from shippers and supply offered by carriers are allowed to vary due to their internal factors. How the demand and supply vary with respect to time is not the focus of this research. Instead, the focus is on how a given FF is able to respond to changes of the environment and reactions from other interacting parties.

Settings for the three shippers are presented in Table 5.7. Each shipper has its own demand for cargo movement and selection behavior for the preferred FF. Each shipper's demand of cargo movement varies with respect to time and follows uniform distribution (only discrete values are valid for demand).

Table 5.7 Settings for shipper agents (Expt. 5b)

Shipper	Type	Demand	Demand	Specifications
SP_1	B	$uniform(250 \pm 40) TEUs$	255 TEUs	Lowest price
SP_2	C	$uniform(200 \pm 40) TEUs$	200 TEUs	Price sensitivity =0.06;
SP_3	B	$uniform(225 \pm 40) TEUs$	225 TEUs	Lowest price

1) Type A: Do not choose the FF who offers the highest or the lowest price; Randomly choose one FF among all the other FFs;
2) Type B: Prefer the FF who offers the Lowest price
3) Type C: Modeled by the multi-nominal logit model (discussed in Section 3.3.2.2)

Settings for the four carriers are presented in Table 5.8. The first two carriers use liner freight rate scheme and the latter two use stepwise freight rate scheme. It is assumed that the capacity of carriers varies with respect to time and follows uniform distribution (only discrete values are valid for available slots).

It is assumed that both FFs are able to learn: FF_1 learns by Q-learning and FF_2 learns on if-then basis. Table 5.9 presents how action space, possible markup points, and states (only for the FF who learns by reinforcement learning) are defined in this experiment.

Table 5.8 Settings for carrier agents (Expt. 5b)

Carrier	Type	Parameters
C_1	A+C	$y = 800 - 0.5x;$ $capacity = uniform(300 \pm 25)\ TEUs$
C_2	A+D	$y = 600 - 0.3x;$ $capacity = uniform(290 \pm 25)\ TEUs$
C_3	B+C	$price_1 = 750; price_2 = 600; V_1 = 125;$ $capacity = uniform(310 \pm 25)\ TEUs$
C_4	B+D	$price_1 = 700; price_2 = 650; V_1 = 150;$ $capacity = uniform(320 \pm 25)\ TEUs$

*Type A: linear pricing scheme
*Type B: step-wise pricing scheme
*Type C: prefer FFs who offer larger volume of cargo
*Type D: prefer FFs who offer higher price

Table 5.9 Settings for FF agents (Expt. 5b)

FF	Type	Specifications
FF_1	B4: Q learning	$min\ markup = 0\%; max\ markup = 300\%;$ $markup_1 = 100\%;\ markup_2 = 200\%;$ $MS_1 = 33\%;\ MS_2 = 66\%;$ $mp = 3$ (9 possible markup points)
FF_2	C: If-then basis	$min\ markup = 0\%; max\ markup = 300\%;$ 9 possible markup points (same as FF_1)

B4: Q learning
C: Learn on if then basis presented in Section 4.3.2.

An extensive search was conducted to find the optimal setting for the parameters associated with the learning model associated with each FF. For each combination of settings for parameters, the experiment is run for 20 runs and each run lasts for 500 iterations. The best setting for the parameters associated with each FF is presented in Table 5.10. The pricing performance (averaged over 20 runs of 500 iterations each) of FF_1 and FF_2 under the best setting for learning parameters is presented in Fig. 5.24 (total profit) and Fig. 5.25 (total volume of cargo obtained). By conducting statistical analysis, 20 simulation runs are sufficient and we can conclude that:

First of all, reinforcement learning helps improve a FF's pricing performance vis-à-vis a FF who learns on if then basis even when demand and supply in the market vary with time. A FF is able to improve its pricing performance by properly defining its state and action space even though the demand and supply vary with respect to time.

In addition, the simulation result further confirms the conclusion we drawn from Expt. 5a (Section 5.4.2.1): whether a FF can achieve its optimal pricing performance is determined by its capability to beat its competitors via learning. In this experiment, although demand and supply are allowed to vary, the best setting for the learning parameters associated with both FFs still remains unchanged (same as Expt. 5a). As a result, no matter how the market condition and the behavior of shippers/carriers changes, a FF is able to assure its profitability by efficient learning and competition with other competing FFs.

Another similar conclusion (as discussed in Section 5.4.2.1, Expt. 5a) can also be drawn in this experiment: the total profit earned by a FF is a result of balancing revenue, cost, and volume. For a specific simulation run under the best setting for the learning model parameters, the variation of demand and supply is presented in Fig. 5.26. Although the demand and supply are allowed to very, there is still over supply in the market. The total revenue gained by FF_1 and FF_2 is presented in Fig. 5.27. The total cost of both FFs (Fig. 5.28) keeps increasing, but the FF who learns by Q-learning (FF_1) performs better in terms total profit (Fig. 5.29). Although FF_1 bears higher total cost (Fig. 5.28), its total profit (Fig. 5.29) and total volume of cargo (Fig. 5.30) still outperform FF_2 . FF_1 also obtain higher market share than FF_2 (Fig. 5.31). on the other hand, although FF_1 gains higher total profit (Fig. 5.29), it does not beat FF_2 in terms of average unit cargo revenue (Fig. 5.32) and average unit cargo profit (Fig. 5.34). The average unit cargo cost for both FFs are around the same level (Fig. 5.33).

Table 5.10 Best setting for FFs' learning model parameters (Expt. 5b)

FF	Type	Specifications
FF_1	B4: Q learning	$\alpha = 0.30, \gamma = 0.05$
FF_2	C: If-then basis	$ag_i = 0.80$

B4: Q learning
C: Learn on if then basis presented in Section 4.3.2.

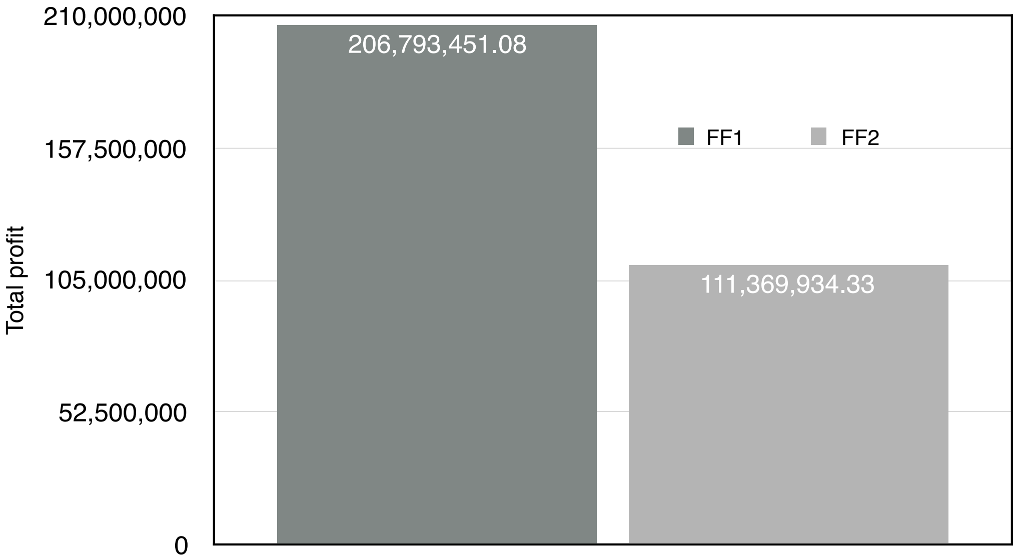

Fig. 5.24 Pricing performance of FF_1 and FF_2 –total profit earned

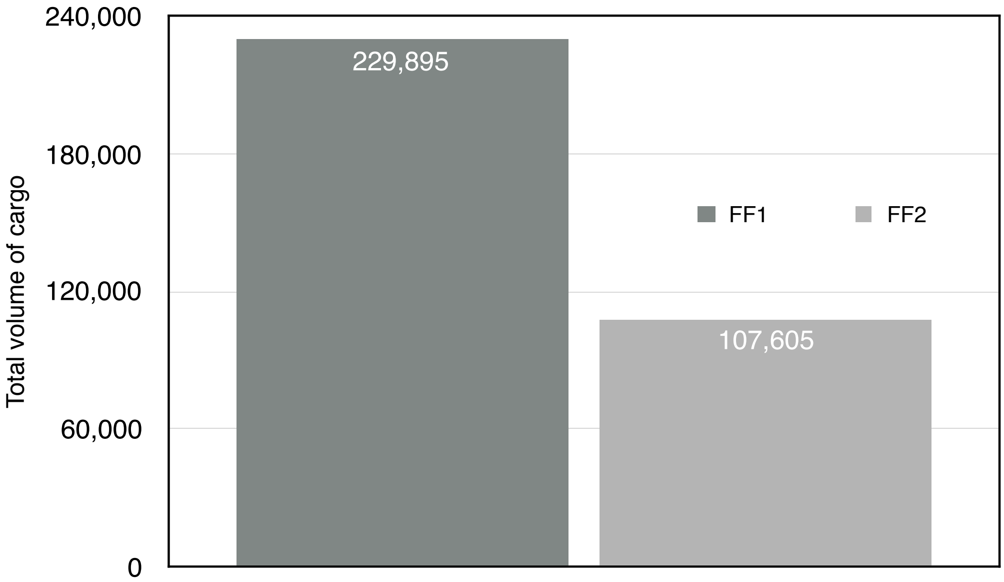

Fig. 5.25 Pricing performance of FF_1 and FF_2 – volume of cargo obtained

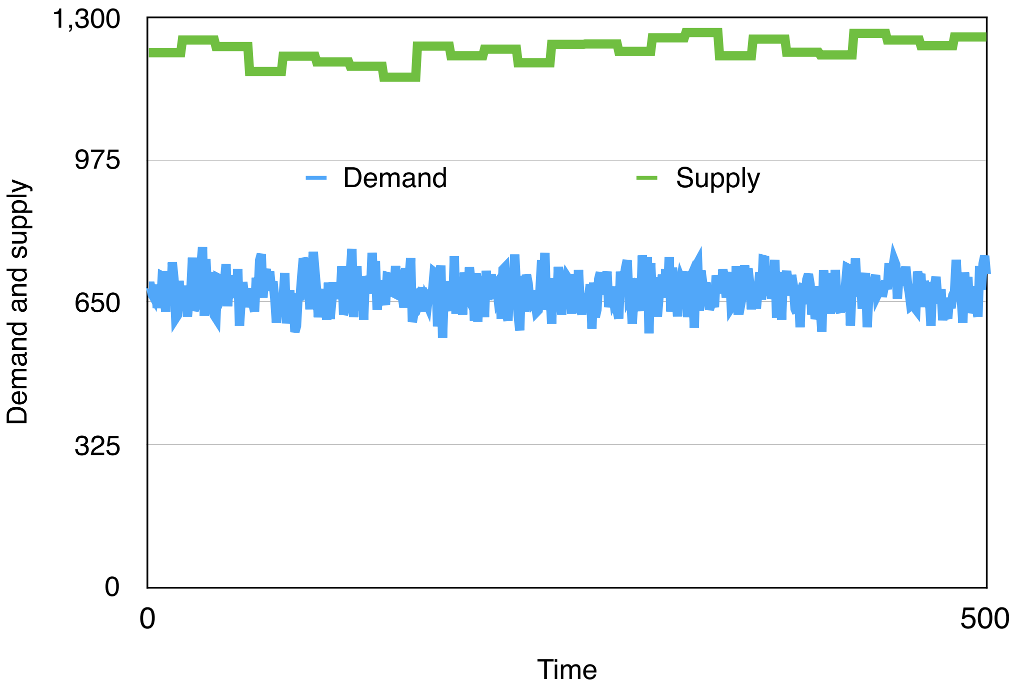

Fig. 5.26 Variation of demand and supply

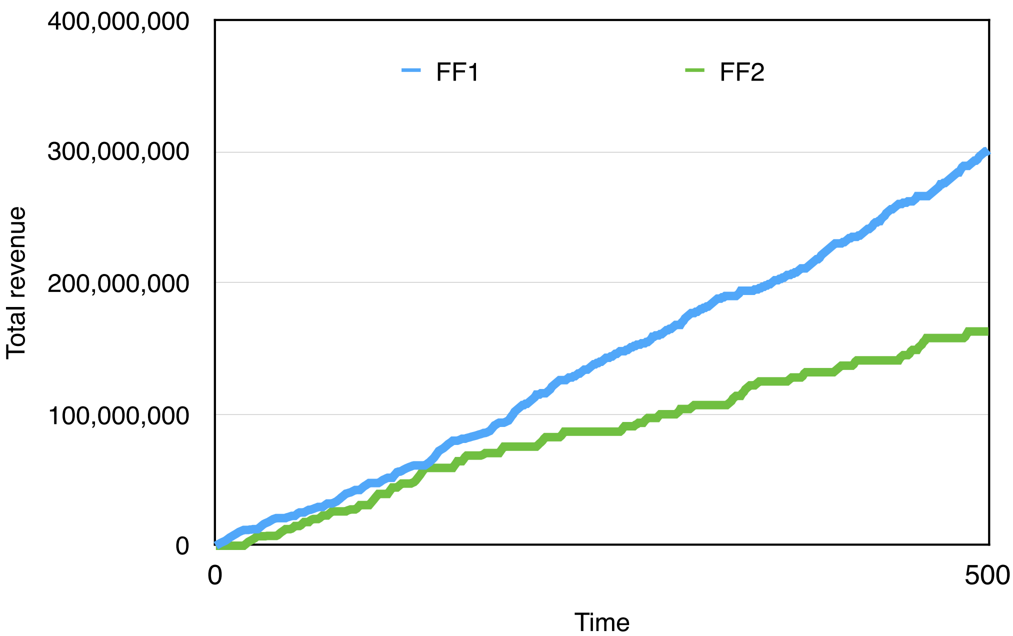

Fig. 5.27 Total revenue earned by FF_1 and FF_2

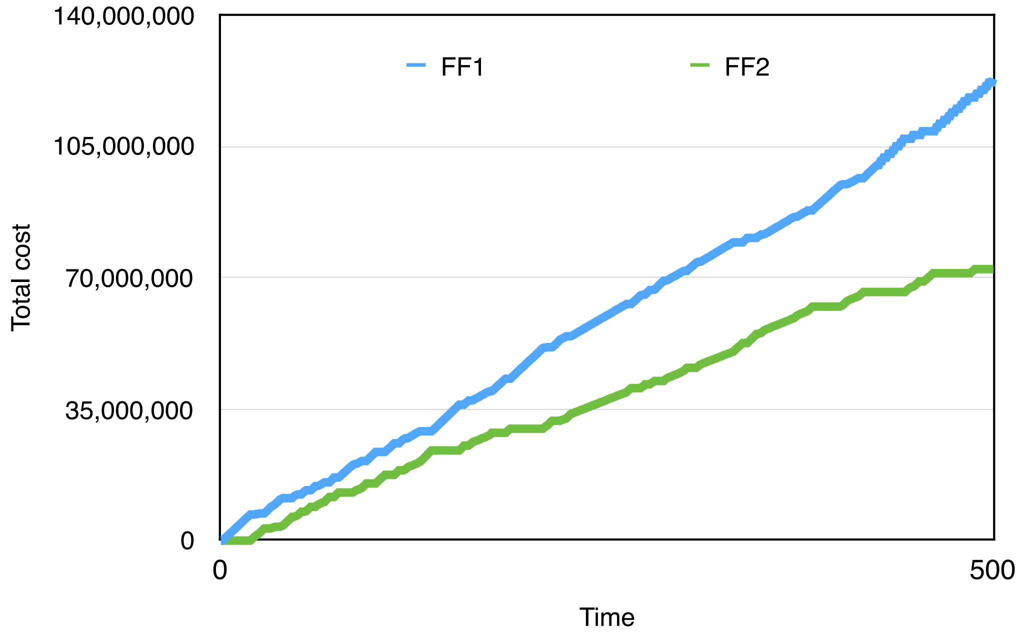

Fig. 5.28 Total cost of FF_1 and FF_2

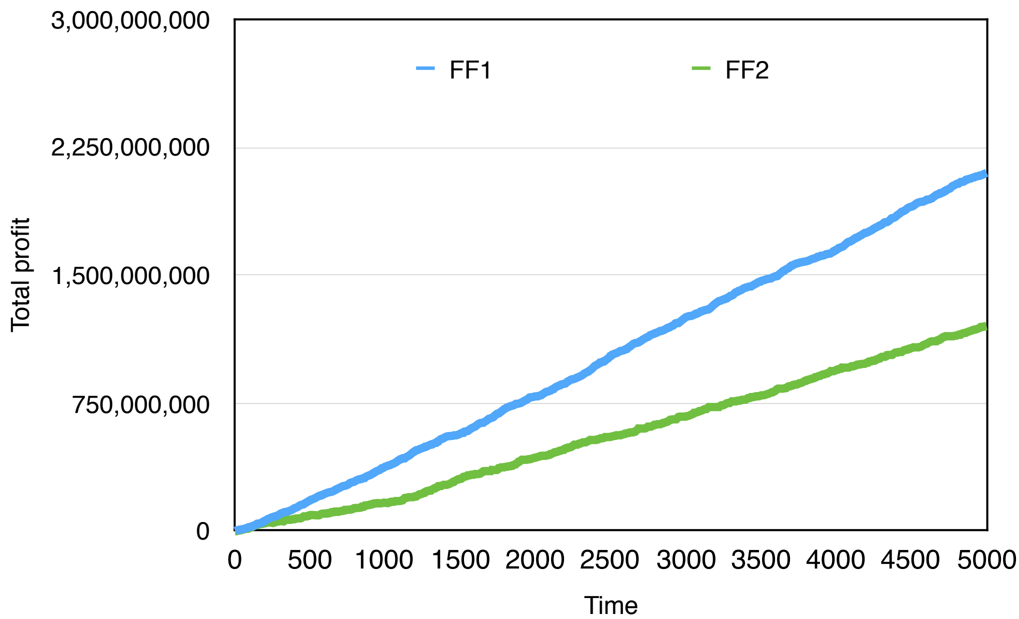

Fig. 5.29 Total profit obtained by FF_1 and FF_2

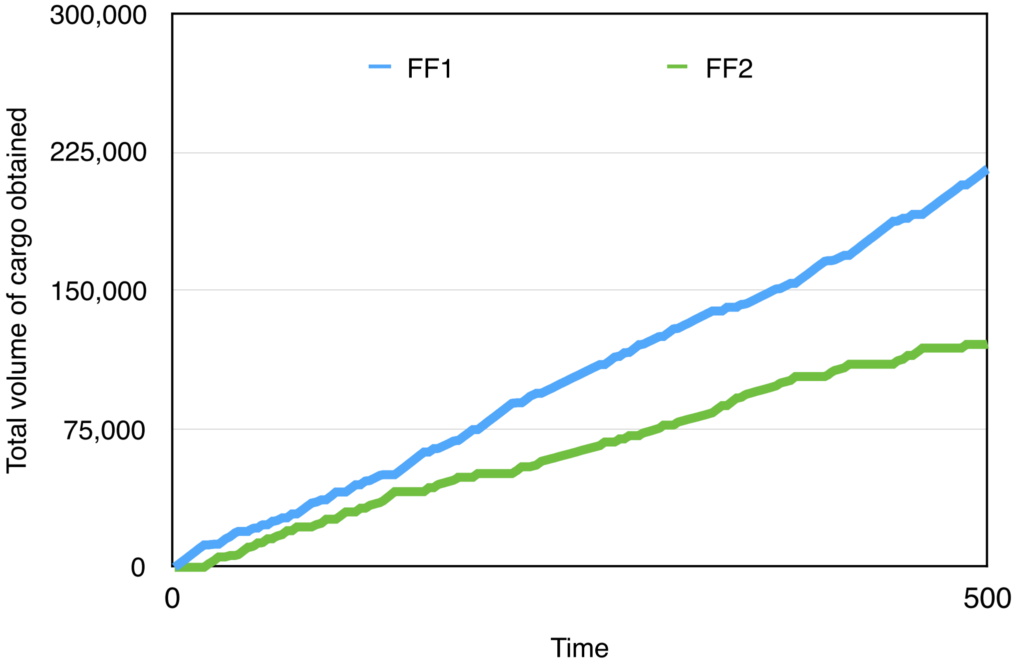

Fig. 5.30 Total volume of cargo earned by FF_1 and FF_2

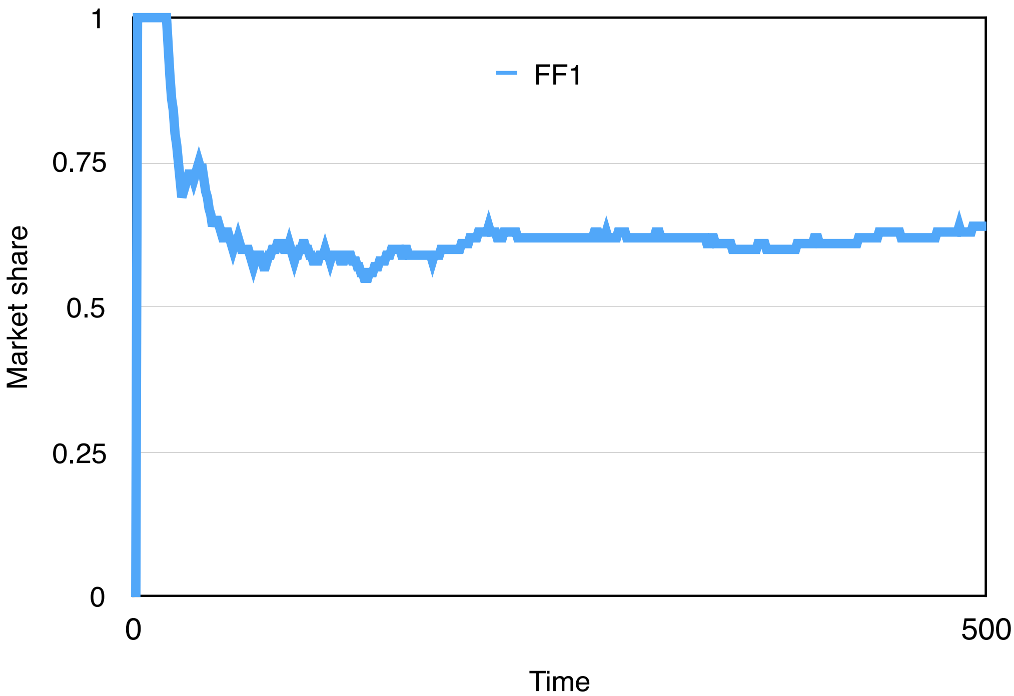

Fig. 5.31 Market share of FF_1

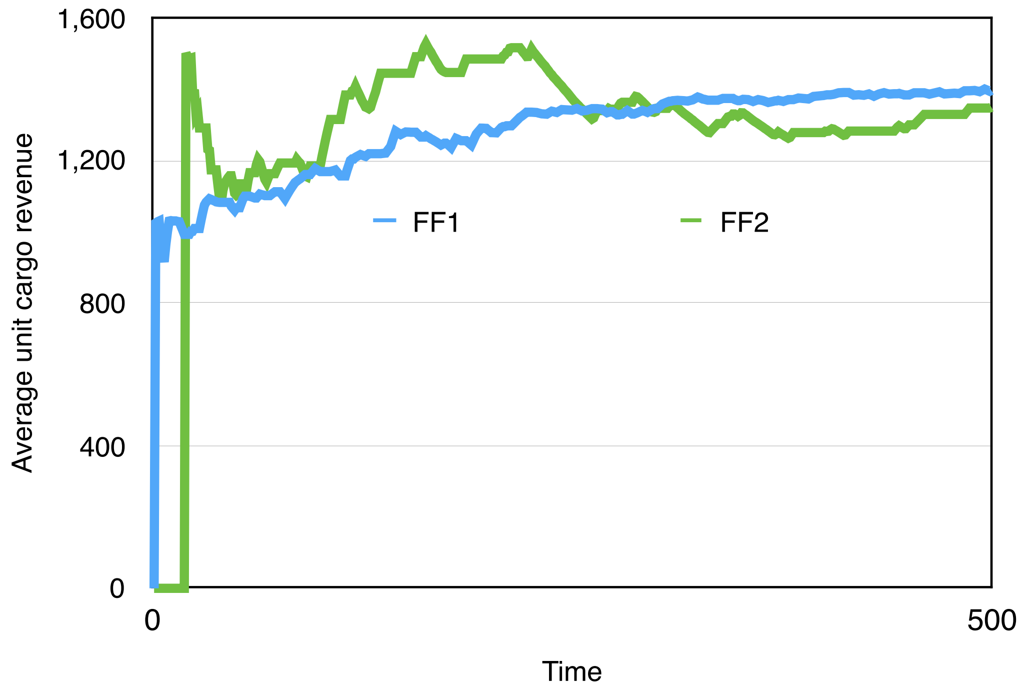

Fig. 5.32 Average unit cargo revenue of FF_1 and FF_2

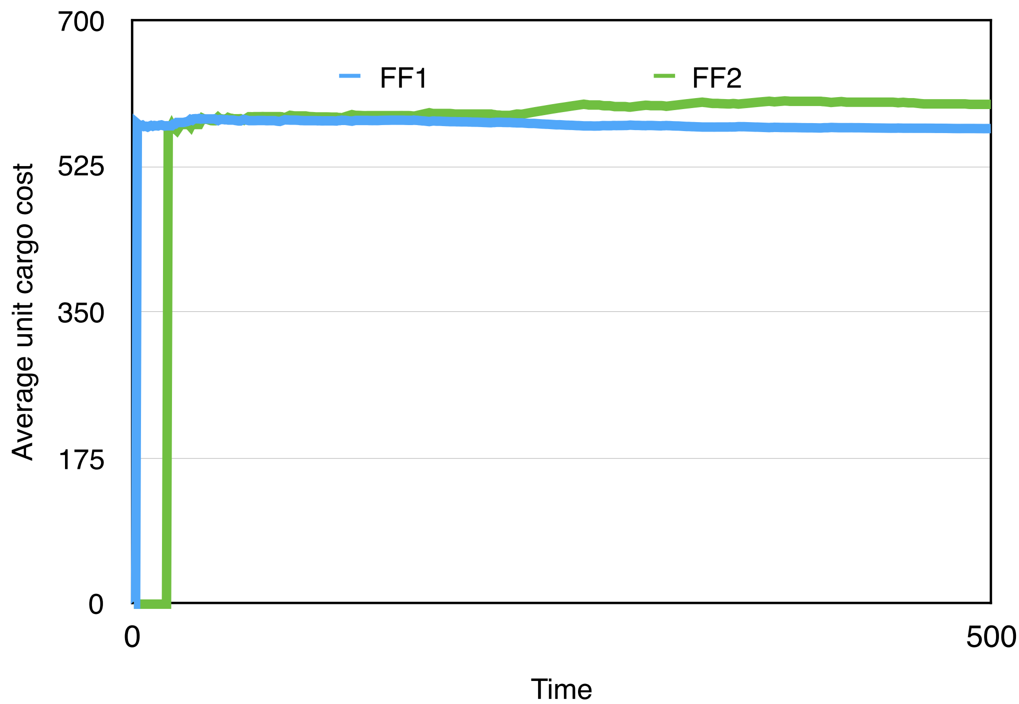

Fig. 5.33 Average unit cargo cost of FF_1 and FF_2

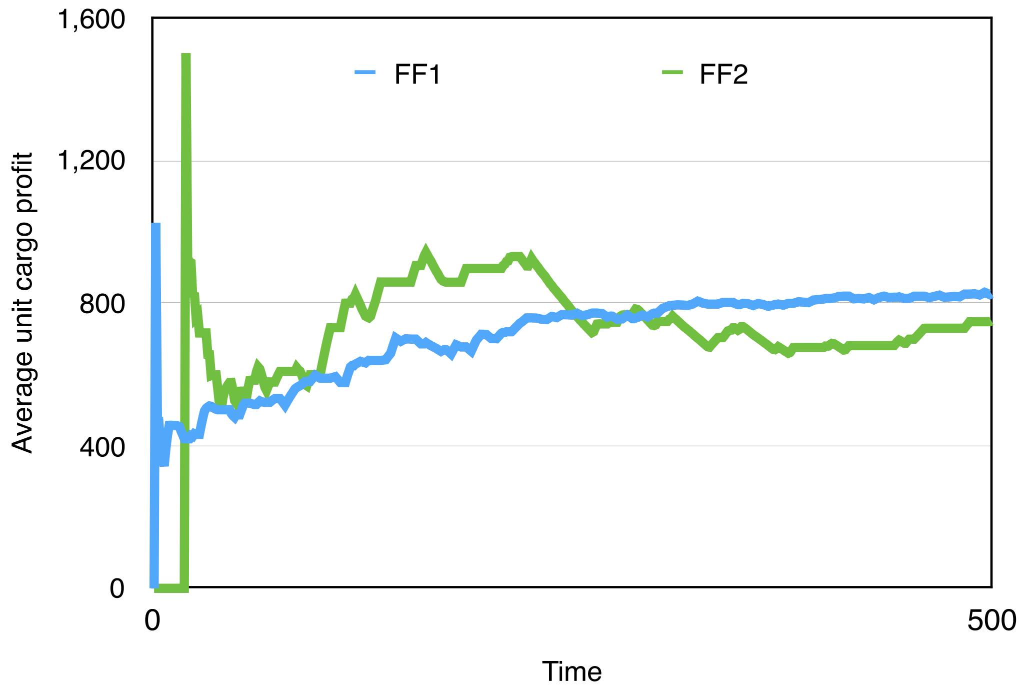

Fig. 5.34 Average unit cargo profit of FF_1 and FF_2

5.4.3 Asynchronous Time Model

With the asynchronous time model assumption, the whole analysis horizon is assumed to last for N simulation time. There is no "grid" on time axis and events may occur at arbitrary moments, exactly when they are to occur.

5.4.3.1 Experiment 5c: flexible demand and supply with two FFs

In this experiment, the aim is to investigate the performance of RL models when the synchronous time model assumption is relaxed. Instead, the simulation time is assumed to be continuous and each activity happens at exactly the moment when it is to occur. By extending the experiment conducted in Section 5.4.2.2

(Expt. 5b), the investigation still focuses on the interaction between three shippers ($SP_k, k = 1,2,3$), two FFs ($FF_i, i = 1,2$), and four carriers ($C_j, j = 1,2,3,4$). The demand and supply in the market are also allowed to vary.

Settings for the three shippers remain unchanged as presented in Table 5.7 (Expt. 5b, Section 5.4.2.2). Each shipper has its own demand for cargo movement and selection behavior for preferred FFs. Their respective demand for cargo movement varies with respect to time and follows the uniform distribution (only discrete values are valid for the demand at a given time point). Further in this experiment, the demand for cargo movement from a specific shipper is generated at a given time interval of 1 simulation time and repeats throughout the entire simulation horizon – 500 simulation time. In addition, after sending solicitations to all FFs, a shipper will wait for responses from all FFs until: 1) responses from all FFs are received (transition t_3 shown in Fig. 5.35); or 2) a maximum time period has been waiting for - whichever happens first. The above maximum time period can be interpreted as a shipper's patience when choosing a FF, and the above "patience" is assumed to follow uniform distribution ($patience \in uniform(0,1]$). In the end, the shipper offers all its cargo to the selected FF. Setting for shipper agents is summarized in Table 5.11.

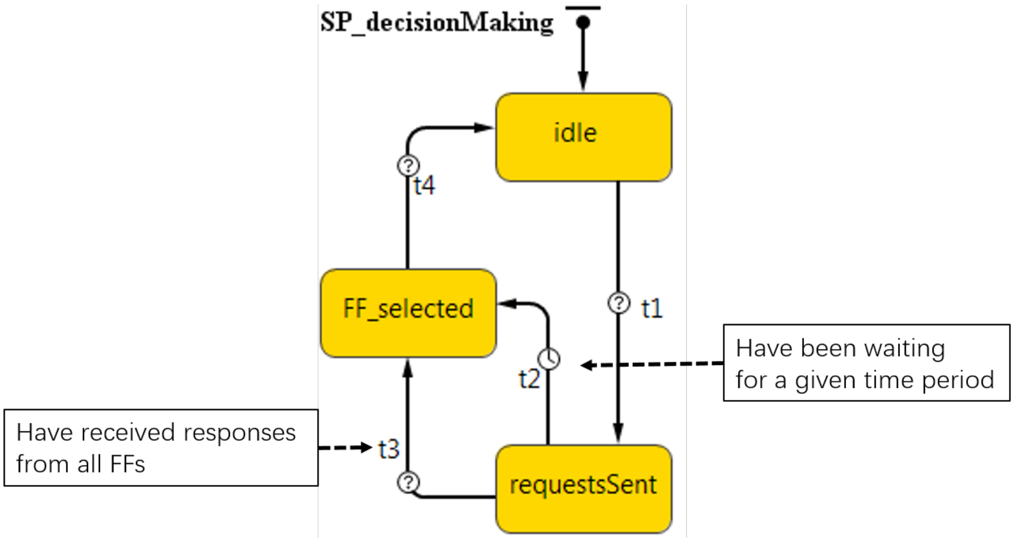

Fig. 5.35 The statechart of a FF agent – an asynchronous time model

Table 5.11 Settings for shipper agents (Expt. 5c)

Shipper	Type	Demand	Patience	Price sensitivity
SP_1	B	$uniform(250 \pm 40) TEUs$	$uniform(0.5,1)$	NA
SP_2	C	$uniform(200 \pm 40) TEUs$	$uniform(0.5,1)$	0.06;
SP_3	B	$uniform(225 \pm 40) TEUs$	$uniform(0.5,1)$	NA

1) Type A: Do not choose the FF who offers the highest or the lowest price; Randomly choose one FF among all the other FFs;
2) Type B: Prefer the FF who offers the Lowest price
3) Type C: Modeled by the multi-nominal logit model (discussed in Section 3.3.2.2)

Settings for the four carriers remain unchanged as presented in Table 5.8 (Expt. 5b). Among them, two carriers use liner freight rate scheme and the other two use stepwise freight rate scheme. The capacity of each carrier varies with respect to time and follows the uniform distribution (only discrete values are valid for the available slot at a specific time point). Further in this experiment, it is assumed that after a specific carrier (vessel) calls the port of city A, the carrier will not sail until the expected sailing date (the waiting time of a carrier at port A is 0.2 simulation time). Then the carrier will transport received cargo from the origin port (city A) to the destination port (city B). The carrier will be available again at the original port (city A) after a given time period. The above "time period" includes the cargo transport time and the dispatching time, and follows the uniform distribution ∈ [0.5,1]. The carrier is then available again for the next voyage at the original port (port A). Settings for the carrier agents setting is summarized in Table 5.12.

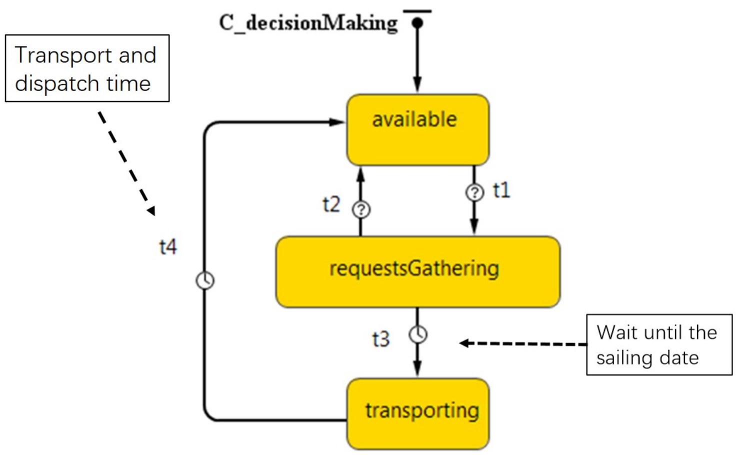

Fig. 5.36 The statechart of a carrier agent – an asynchronous time model

Table 5.12 Settings for carrier agents (Expt. 5c)

Carrier	Type	Parameters
C_1	A+C	$y = 800 - 0.5x;\ capacity = uniform(300 \pm 25)\ TEUs$; waiting time at port = 0.2; $transport\ time\ \&\ dispatching\ time = uniform(0.5,1)$
C_2	A+D	$y = 600 - 0.3x;\ capacity = uniform(290 \pm 25)\ TEUs$; waiting time at port = 0.2; $transport\ time\ \&\ dispatching\ time = uniform(0.5,1)$
C_3	B+C	$price_1 = 750; price_2 = 600; V_1 = 125$; $capacity = uniform(310 \pm 25)\ TEUs; waiting\ time\ at\ port =$ 0.2; $transport\ time\ \&\ dispatching\ time = uniform(0.5,1)$
C_4	B+D	$price_1 = 700; price_2 = 650; V_1 = 150$; $capacity = uniform(320 \pm 25)\ TEUs$; waiting time at port = 0.2; $transport\ time\ \&\ dispatching\ time = uniform(0.5,1)$

*Type A: linear pricing scheme
*Type B: step-wise pricing scheme
*Type C: prefer FFs who offer larger volume of cargo
*Type D: prefer FFs who offer higher price

Settings for the two FFs remain unchanged as presented in Table 5.9 (Expt 5b). Both FFs are able to learn: FF_1 learns by Q-learning and FF_2 learns on if then basis. Further in this experiment, after receiving requests from shippers, it takes time for a FF to estimate the potential cost and then make pricing decisions (Fig. 5.37). The time it takes to process a request can be interpreted as a FF's "efficiency" in processing requests. The above "efficiency" is assumed to follow uniform distribution between [0.2,0.5] simulation time. In addition, after sending cargo split plans to preferred carriers, the FF waits until: 1) all solicitations are responded or; 2) a given time period has been waiting for – whichever happens first (Fig. 5.38). The above time period can be interpreted as the FF's "patience" when interacting with carriers. During simulations, the patience is assumed to be 0.2 simulation time. Table 5.13 summaries settings for the FF agents.

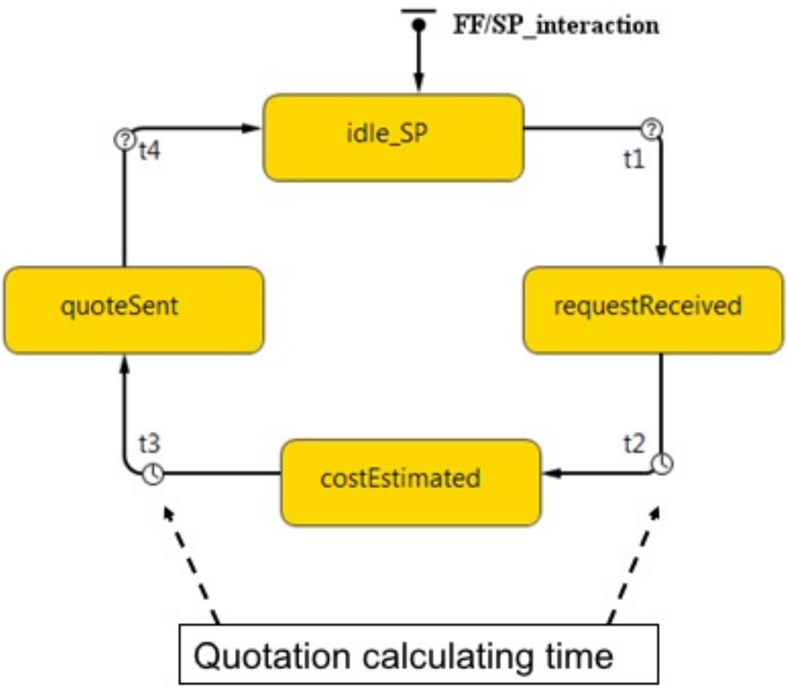

Fig. 5.37 The statechart of a FF agent (interacting with SP) – under asynchronous time model

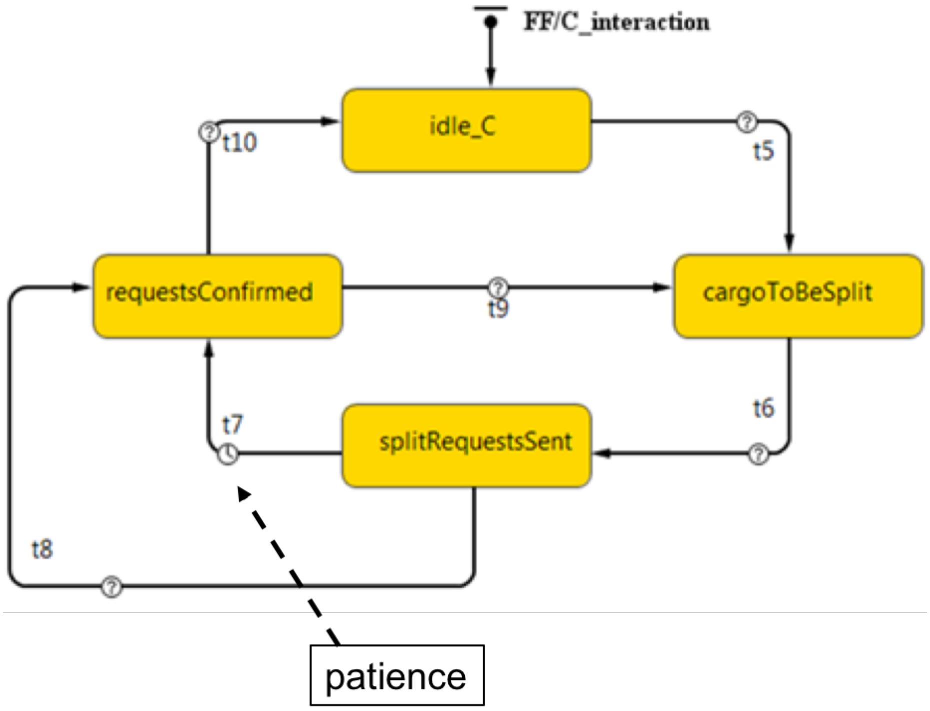

Fig. 5.38 The statechart of a FF agent (interacting with C)– under asynchronous time model

Table 5.13 Settings for FF agents (Expt. 5c)

FF	Type	Specifications
FF_1	B4: Q learning	$min\, markup = 0\%; max\, markup = 300\%$; $markup_1 = 100\%$; $markup_2 = 200\%$; $MS_1 = 33\%$; $MS_2 = 66\%$; $mp = 3$ (9 possible markup points); $efficiency = uniform(0.2,0.50)$; $patience = 0.2$
FF_2	C: If-then basis	$min\, markup = 0\%$; $max\, markup = 300\%$; 9 possible markup points (same as FF_1); $efficiency = uniform(0.2,0.50$; $patience = 0.2$

B4: Q learning
C: Learn on if then basis presented in Section 4.3.2.

An extensive search was conducted to find the optimal setting for the parameters associated with each FF's learning model. For each combination of settings for parameters, the experiment is run for 20 runs and each run lasts for 500 simulation time. The best setting for the parameters associated with FF_1 and FF_2 is presented in Table 5.14. The pricing performance (averaged over 20 runs of 500 simulation time each) of FF_1 and FF_2 under the best setting for the learning parameters is presented in Fig. 5.39 (total profit) and Fig. 5.40 (total volume of cargo obtained). By conducting statistical analysis, 20 simulation runs are sufficient and we can conclude that:

A FF who learns by reinforcement learning can outperform its competitor when simulations are run under the asynchronous time model assumption (Fig. 5.39 and Fig. 5.40). The FF not only gains more profit but also obtains higher market share and volume of cargo. The asynchronous time model assumption can represent the reality in a more realistic manner. The simulation results derived through the interaction between shippers, FFs, and carriers can bring more practical insights for FFs.

Table 5.14 The best setting for FFs' learning model parameters (Expt. 5c)

FF	Type	Specifications
FF_1	B4: Q learning	$\alpha = 0.30, \gamma = 0.05$
FF_2	C: If-then basis	$ag_i = 0.80$

B4: Q learning
C: Learn on if then basis presented in Section 4.3.2.

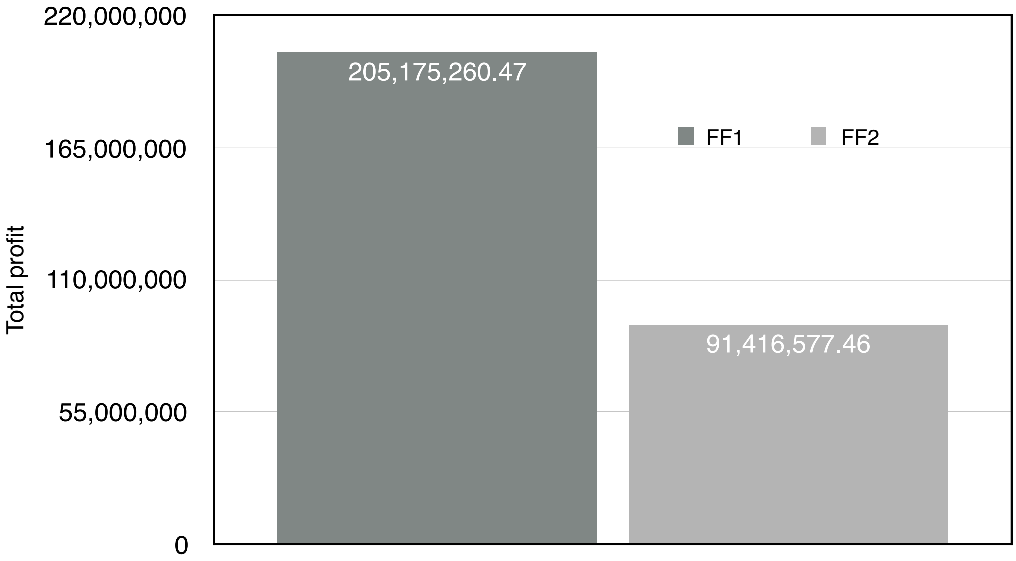

Fig. 5.39 Pricing performance of FF_1 and FF_2 –total profit earned

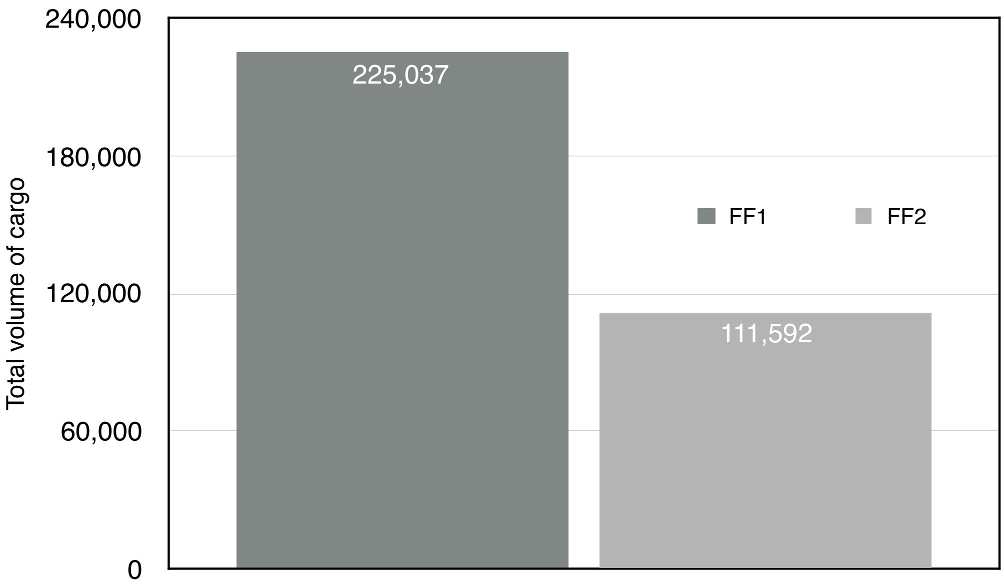

Fig. 5.40 Pricing performance of FF_1 and FF_2 – volume of cargo obtained

By examining a specific simulation run under the best setting for the learning model parameters, similar conclusions can be drawn as discussed in Section 5.4.2.1 (Expt. 5b): the total profit earned by a FF is a result of balancing revenue, cost, and volume. The total profit (Fig. 5.41) earned by a FF is the difference between its total revenue (Fig. 5.42) and total cost (Fig. 5.43). On the one hand, although the total profit earned by FF_1 is higher than that earned by FF_2 throughout the entire simulation horizon (Fig. 5.41), FF_1 does not beat FF_2 in terms of average unit cargo revenue (Fig. 5.44) and average unit cargo profit (Fig. 5.45). On the other hand, the average unit cargo cost for both FFs are around the same level (Fig. 5.46), but FF_1 beats FF_2 in terms of volume (Fig. 5.47) and market share (Fig. 5.47). As a result, the combination effect of average unit cargo revenue (price), volume and average unit cargo cost make FF_1 earn more total profit than FF_2.

By examining the same simulation run discussed above, the result further confirms the conclusion we obtained by conducting Expt. 5a (Section 5.4.2.1) and 5b (Section 5.4.2.2): no matter how market conditions and the behavior of shippers/carriers change, a FF is able to assure its profitability as long as the FF can beat its competitor via competition. For the above simulation run, the variation of total demand and total supply is plotted in Fig. 5.49. Although the total demand and supply are no longer fixed and for a very short time period undersupply may exist, the FF who learns by the Q-learning method still outperforms the other FF who learns on if them basis. As a man in the middle, a FF may not be able to influence the general level of demand and supply, and the FF may not be able to control anyone by himself. However, the FF can learn its competitors' behavior and then adjust its actions accordingly. In this way, better pricing performance can be achieved by learning.

By examining how demand and supply vary over time (Fig. 5.49), we notice that there are short periods of undersupply in the market. This is because when a carrier is on its way transporting cargo from the origin to the destination, the available capacity in the market decreases. Once the available capacity in the market can not serve the demand from all shippers, undersupply occurs. As a result, this experiment also takes into account short periods of undersupply in the market although the market is oversupplied over the long analysis horizon.

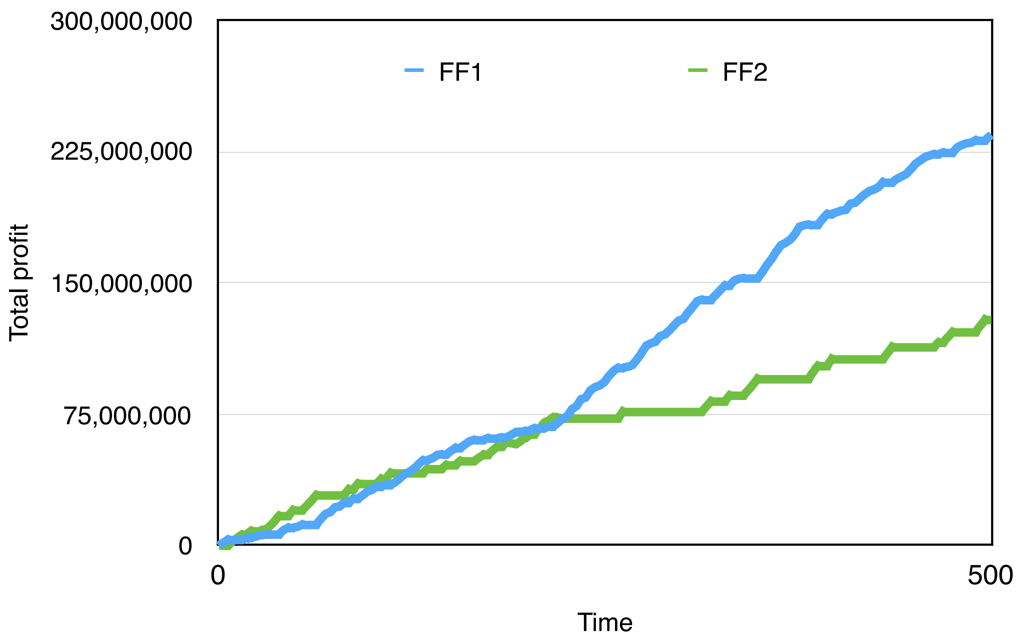

Fig. 5.41 Total profit earned by FF_1 and FF_2

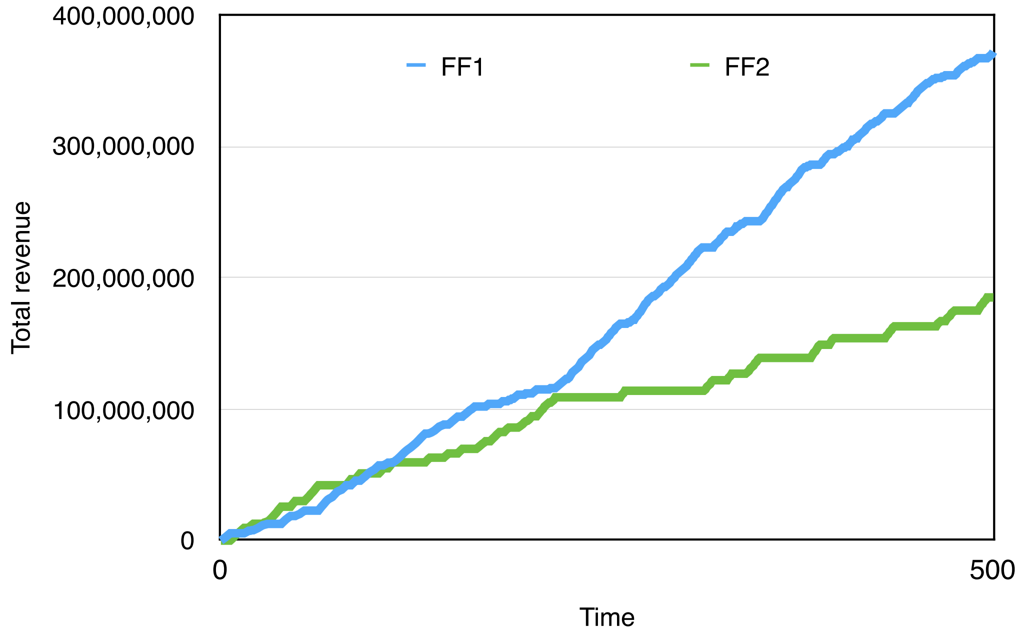

Fig. 5.42 Total revenue earned by FF_1 and FF_2

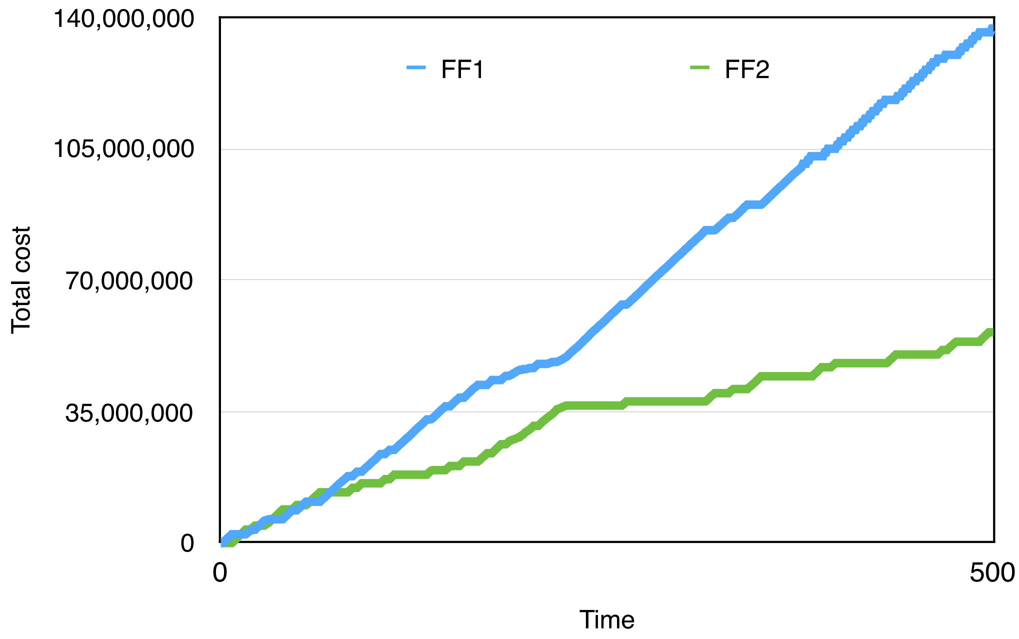

Fig. 5.43 Total cost of FF_1 and FF_2

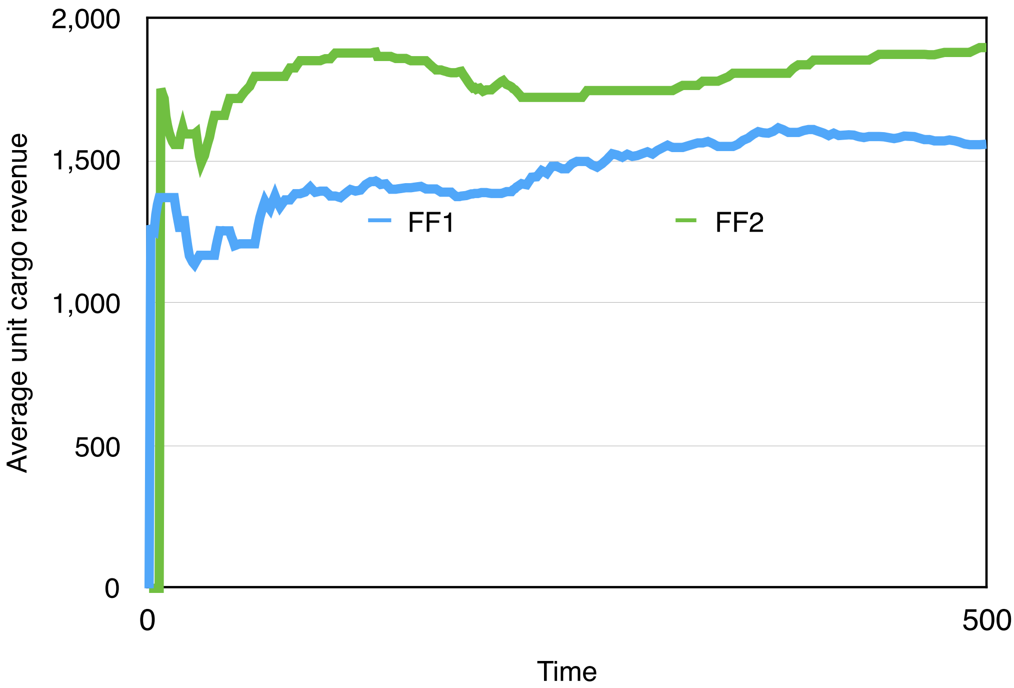

Fig. 5.44 Average unit cargo revenue of FF_1 and FF_2

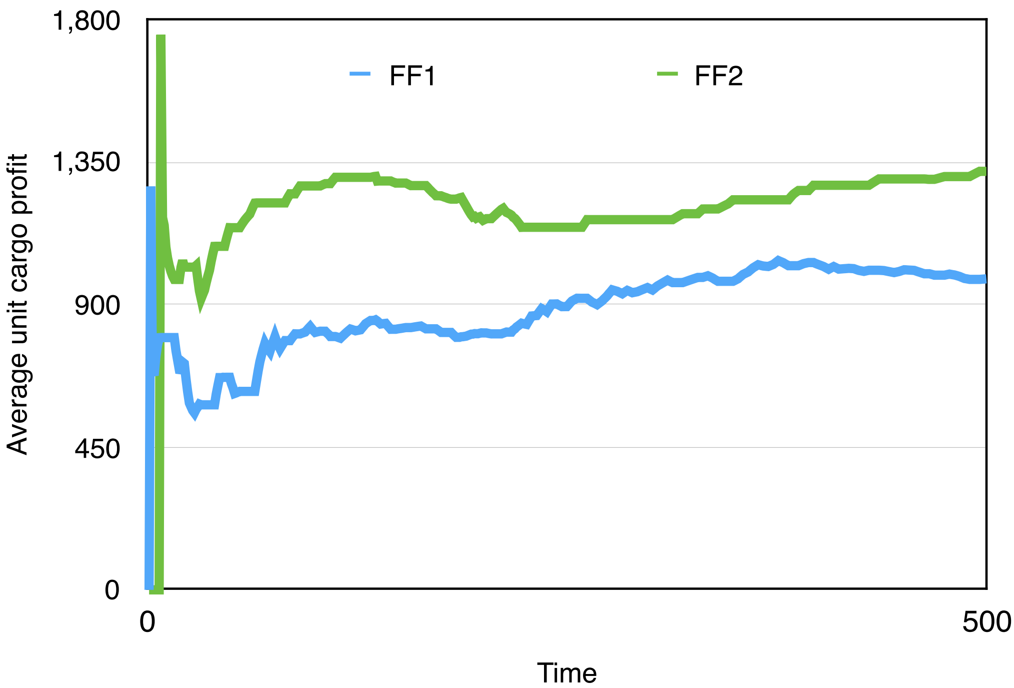

Fig. 5.45 Average unit cargo profit of FF_1 and FF_2

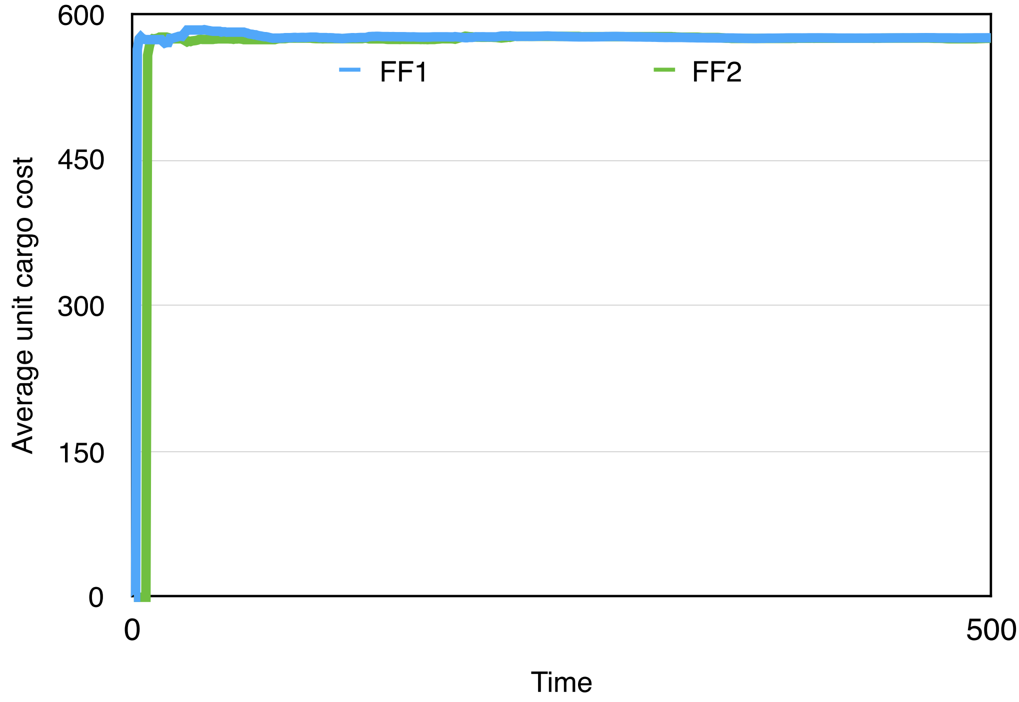

Fig. 5.46 Average unit cargo cost of FF_1 and FF_2

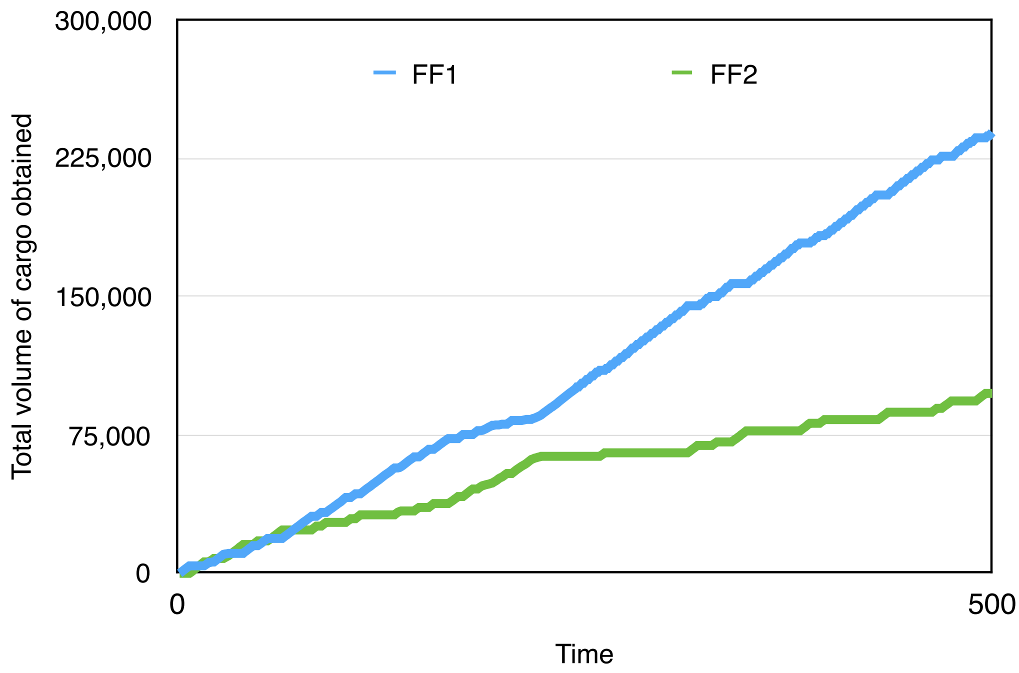

Fig. 5.47 Total volume of cargo earned by FF_1 and FF_2

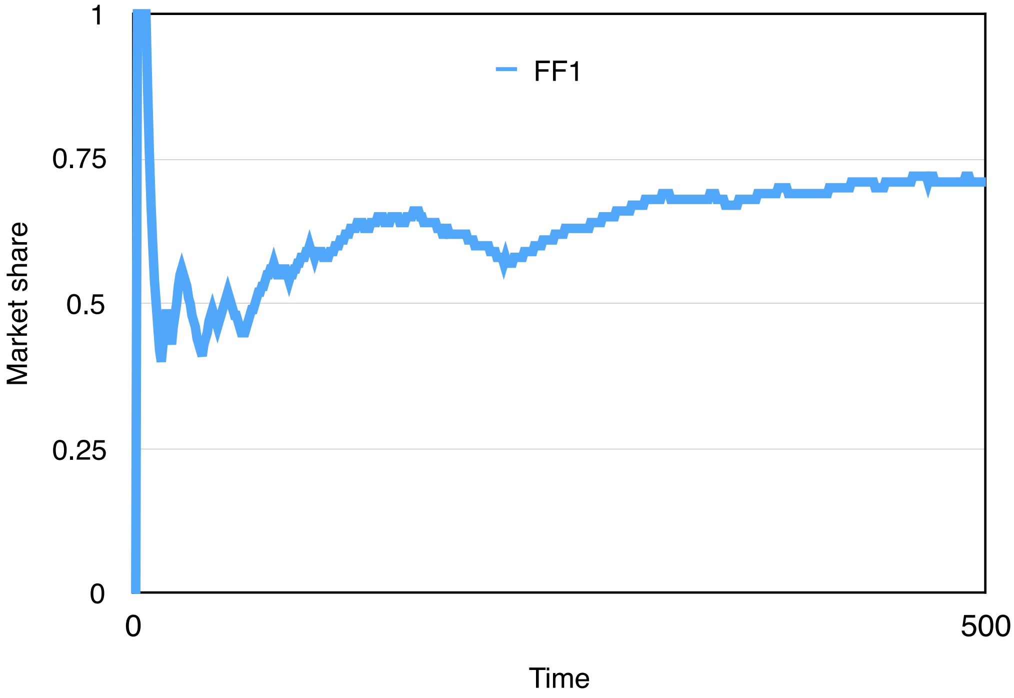

Fig. 5.48 Market share of FF_1

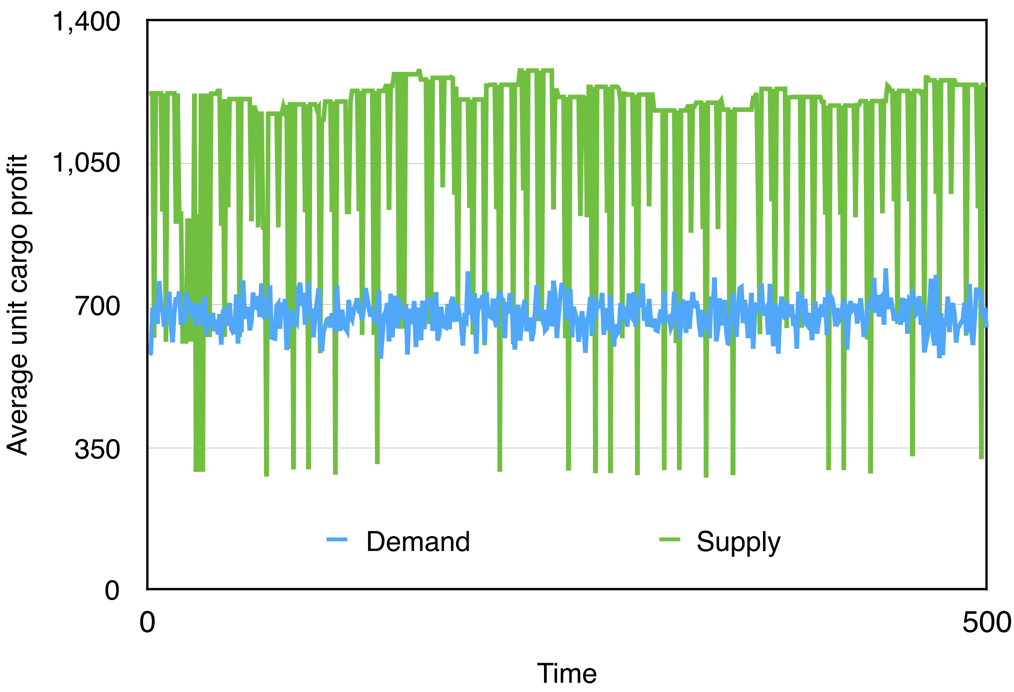

Fig. 5.49 Variation of demand and supply

5.4.3.2 Experiment 5d: flexible demand and multiple FFs

In this experiment, the aim is to investigate the performance of RL models when there are more than two FFs in the market. We extend the experiment conducted in Section 5.4.3.1 (Expt. 5c) by adding three more FFs into the market: the interaction between three shippers ($SP_k, k = 1,2,3$), five FFs ($FF_i, i = 1,2,3,4,5$), and four carriers ($C_j, j = 1,2,3,4$) is investigated. The experiment is conducted under the asynchronous time model assumption. The demand and supply in the market are allowed to vary. Settings for the three shippers and the four carriers remain unchanged as adopted in Section 5.4.3.1 (Expt. 5c, Table 5.11 and Table 5.12).

During multi-agent simulations, all five FFs are able to learn and settings for the learning parameters associated with each FF are presented in Table 5.15: FF_1 learns on if then basis; FF_2 learns by action value method; FF_3 learns by softmax method; FF_4 learns by Sarsa method; and FF_5 learns by Q-learning method. For the two FFs who learn by associated reinforcement learning models ($FF_i, i = 4,5$, Sarsa and Q-learning), their states and action space are defined in the same way as proposed in Section 5.4.3.1 (Expt. 5c).

Table 5.15 Settings for FF agents (Expt. 5d)

FFs	Type	Specifications
FF_1	B4: Q-learning	$min\,markup = 0\%; max\,markup = 300\%;$ $markup_1 = 100\%;\ markup_2 = 200\%;$ $MS_1 = 33\%;\ MS_2 = 66\%;$ $mp = 3$ (9 possible markup points); $\alpha = 0.3, \gamma = 0.05$ $efficiency = uniform(0.2{,}0.50); patience = 0.2$
FF_2	C: If then	$min\,markup = 0\%; max\,markup = 300\%;$ $9\ possible\ markup\ points;$ $efficiency = uniform(0.2{,}0.50);$ $patience = 0.2; ag = 0.8;$
FF_3	B1: Action value	$min\,markup = 0\%; max\,markup = 300\%;$ $9\ possible\ markup\ points\ (same\ as\ FF_1);$ $efficiency = uniform(0.2{,}0.5);$ $patience = 0.2; greedy = 0.05$
FF_4	B2: Softmax	$min\,markup = 0\%; max\,markup = 300\%;$ $9\ possible\ markup\ points\ (same\ as\ FF_1);$ $efficiency = uniform(0.2{,}0.50);$ $patience = 0.2; \tau = 500$
FF_5	B3: Sarsa	$min\,markup = 0\%; max\,markup = 300\%$ $efficiency = uniform(0.2{,}0.50;$ $patience = 0.2; \alpha = 1, \gamma = 0.05$

Based on the settings presented in Table 5.15, multi agent simulations are conducted with each experiment running for 20 runs and each run lasting for 500 simulation time. The pricing performance (averaged over 20 runs of 500 simulation time each) of all FFs is presented in Fig. 5.50 (total profit) and Fig. 5.51 (total volume of cargo obtained). By conducting statistical analysis, 20 simulation runs are sufficient and we can conclude that:

Associated RL models (Q-learning and Sarsa) perform better than the if then learning model, and they all outperform non-associated RL models (Softmax and Action value). We rank all learning models in terms of pricing performance (total profit earned): Q-leanring > Sarsa > if then > softmax > action value. The simulation results obtained in this experiment also confirms the conclusion we drawn in previous experiments (Expt. 5a, 5b, and 5c): a FF who learns by reinforcement learning can improve their pricing performance by properly defining its states and action space; 2) whether a FF is able to achieve its optimal pricing performance is determined by its capability to beat competitors via learning; and 3) the total profit earned by a FF is a result of balancing revenue, cost and volume. By examining a specific simulation run under the setting for parameters presented in Table 5.15 , we can obtain total revenue (Fig. 5.52), total cost (Fig. 5.53), total profit (Fig. 5.54), market share (Fig. 5.56), unit cargo revenue (Fig. 5.57), unit cargo cost (Fig. 5.58), and unit cargo profit (Fig. 5.59) associated with each FF.

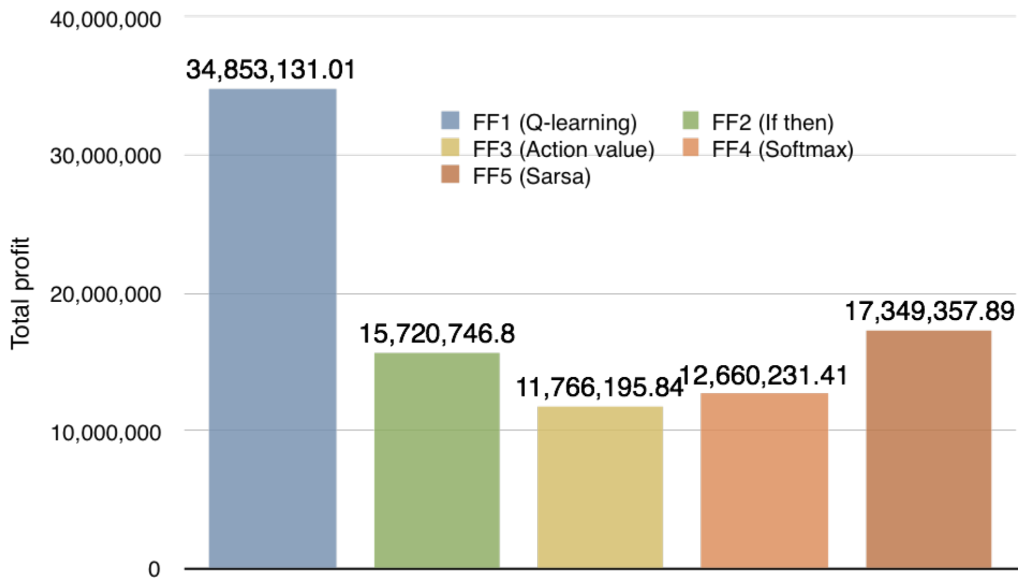

Fig. 5.50 Pricing performance – total profit

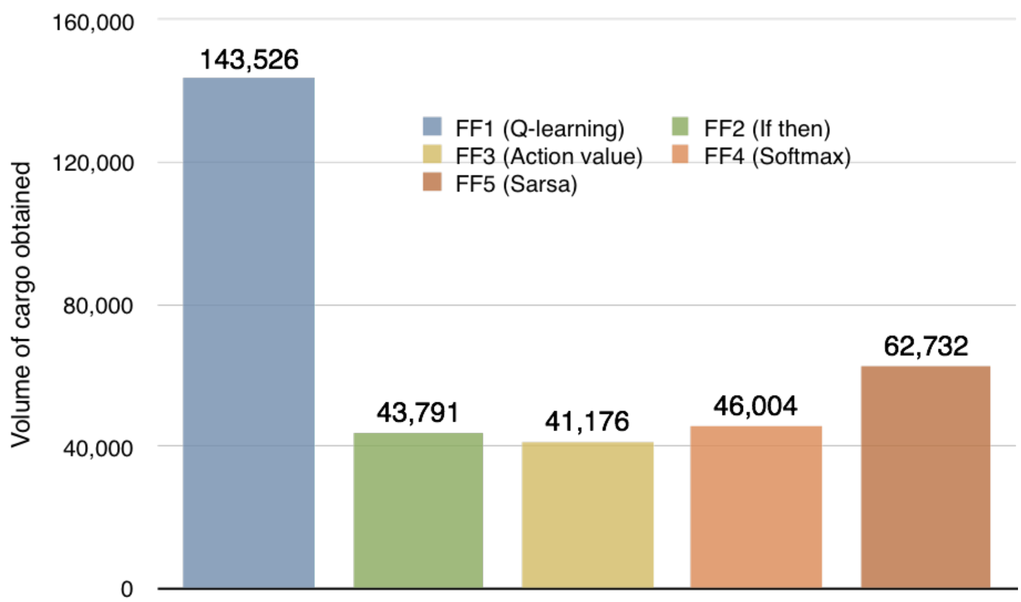

Fig. 5.51 Pricing performance - volume of cargo

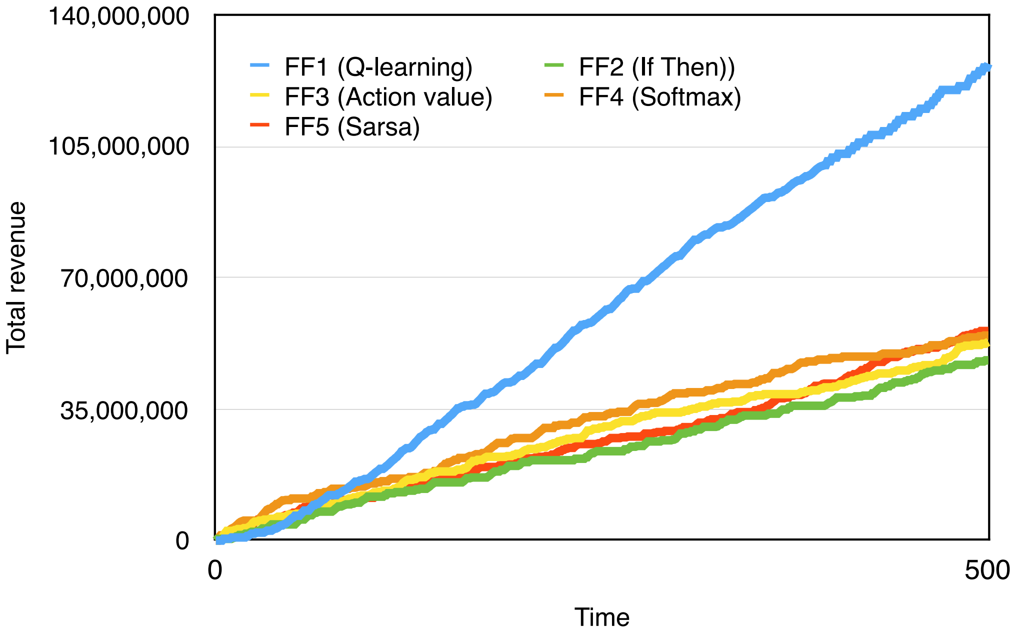

Fig. 5.52 Total revenue obtained by FFs

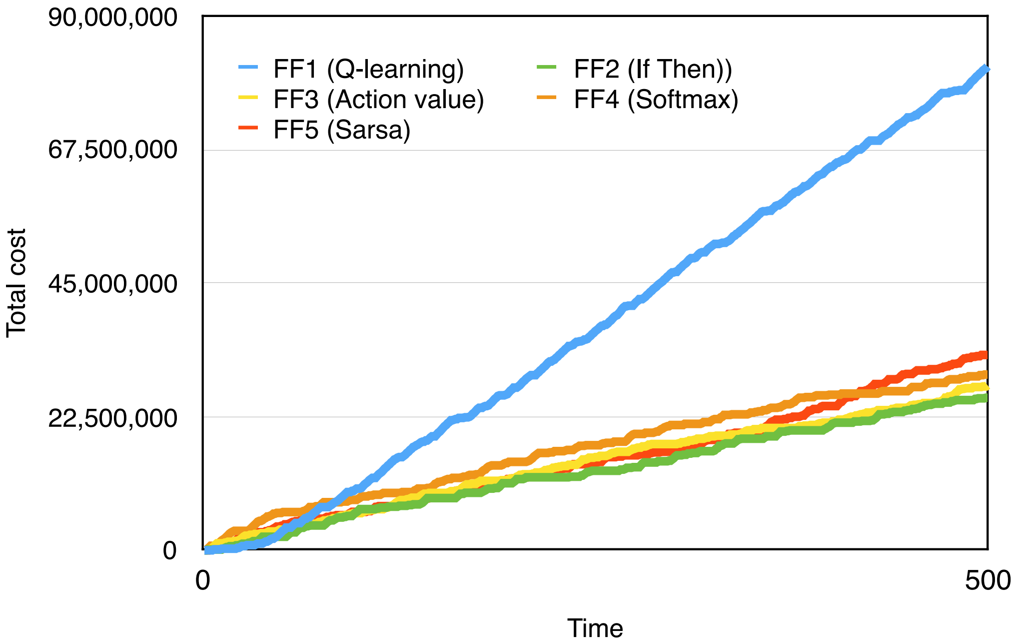

Fig. 5.53 Total cost of FFs

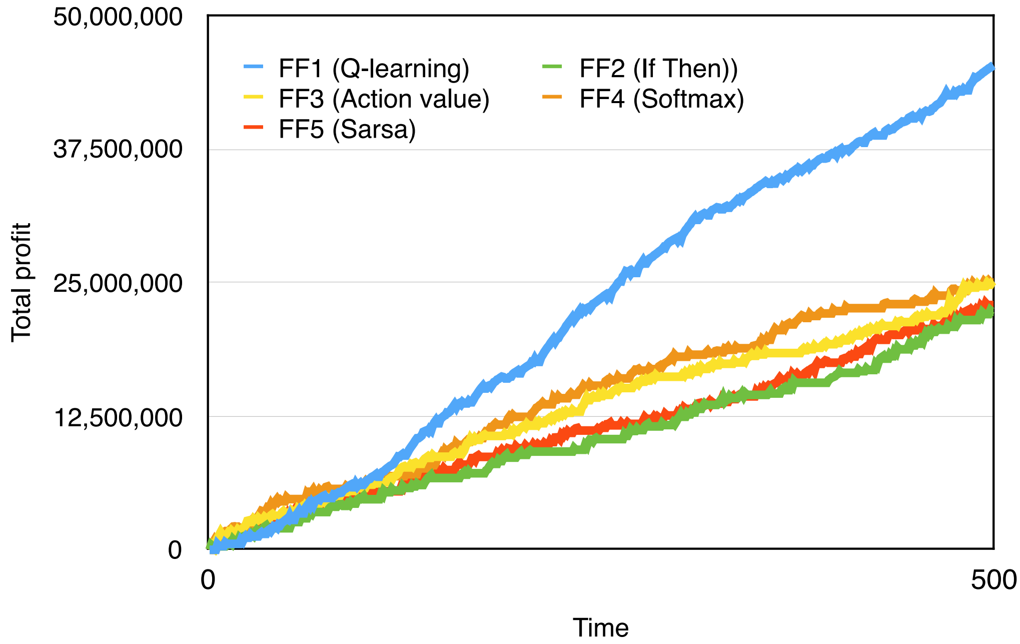

Fig. 5.54 Total profit obtained by FFs

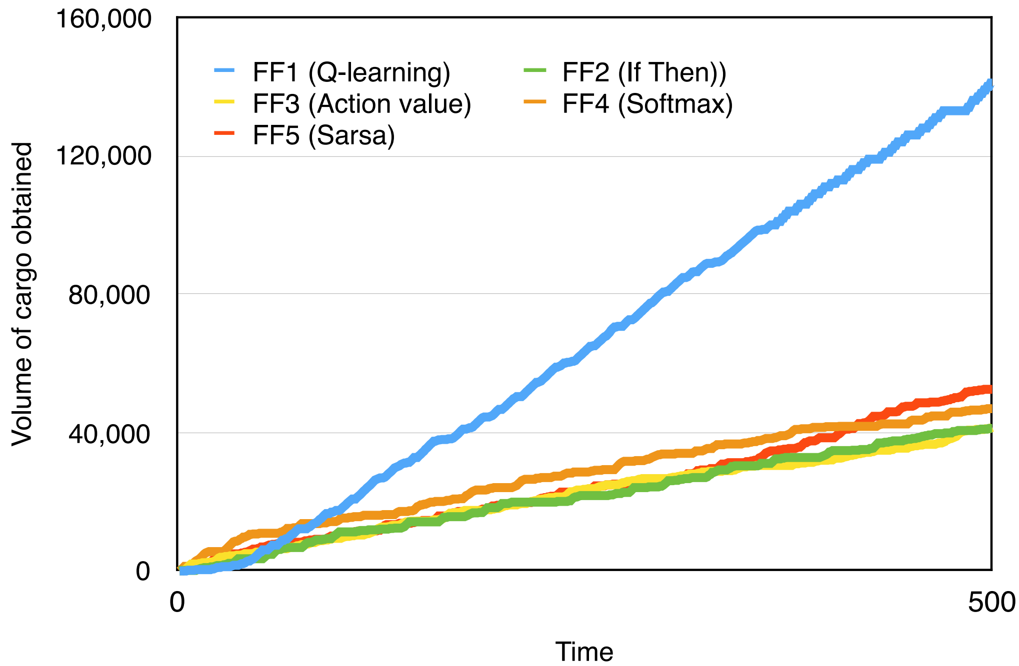

Fig. 5.55 Total volume of cargo obtained by FFs

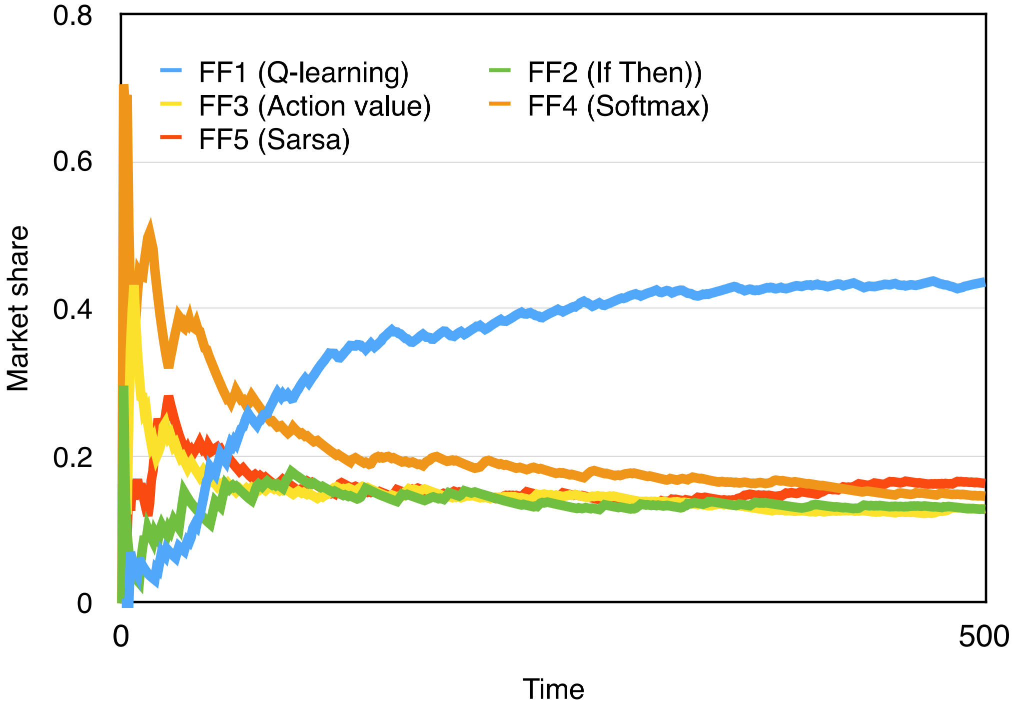

Fig. 5.56 Market share

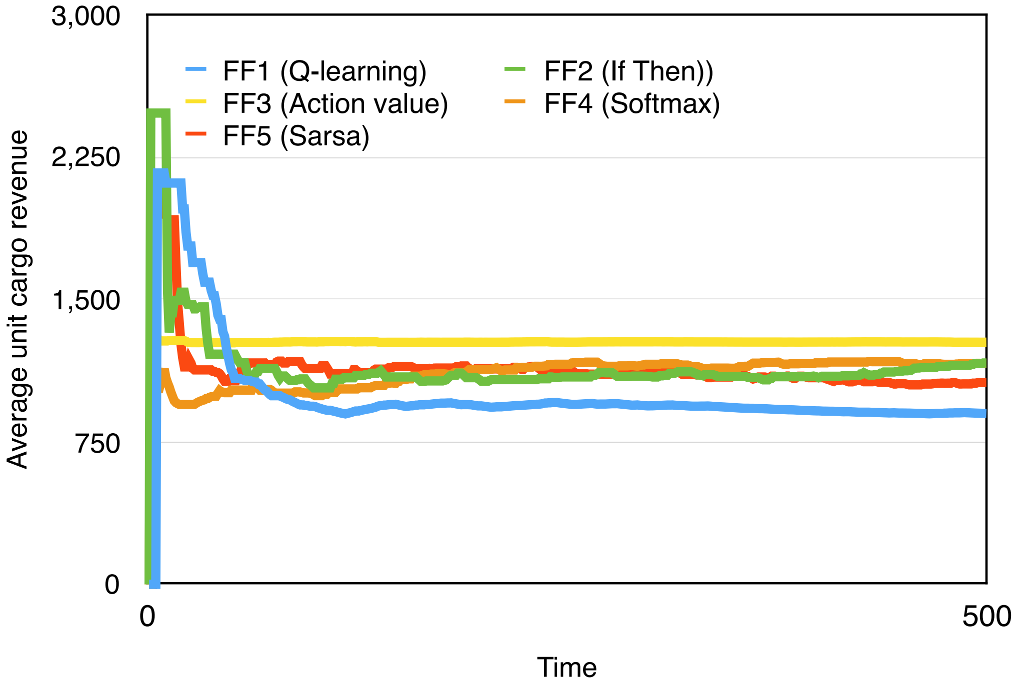

Fig. 5.57 Average unit cargo revenue obtained by FFs

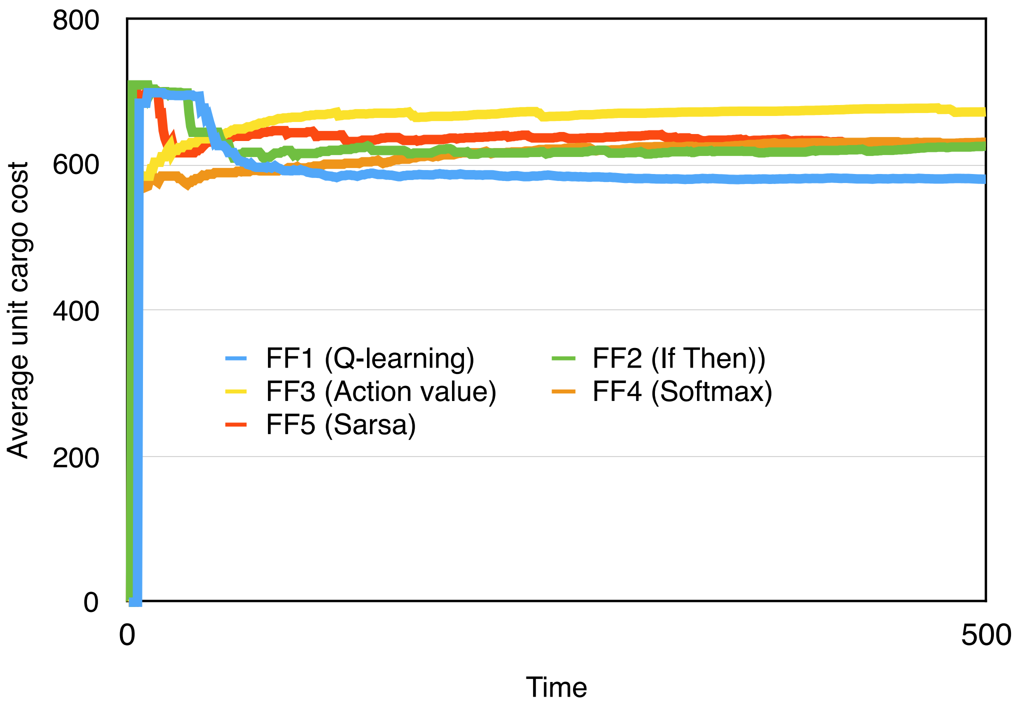

Fig. 5.58 Average unit cargo cost

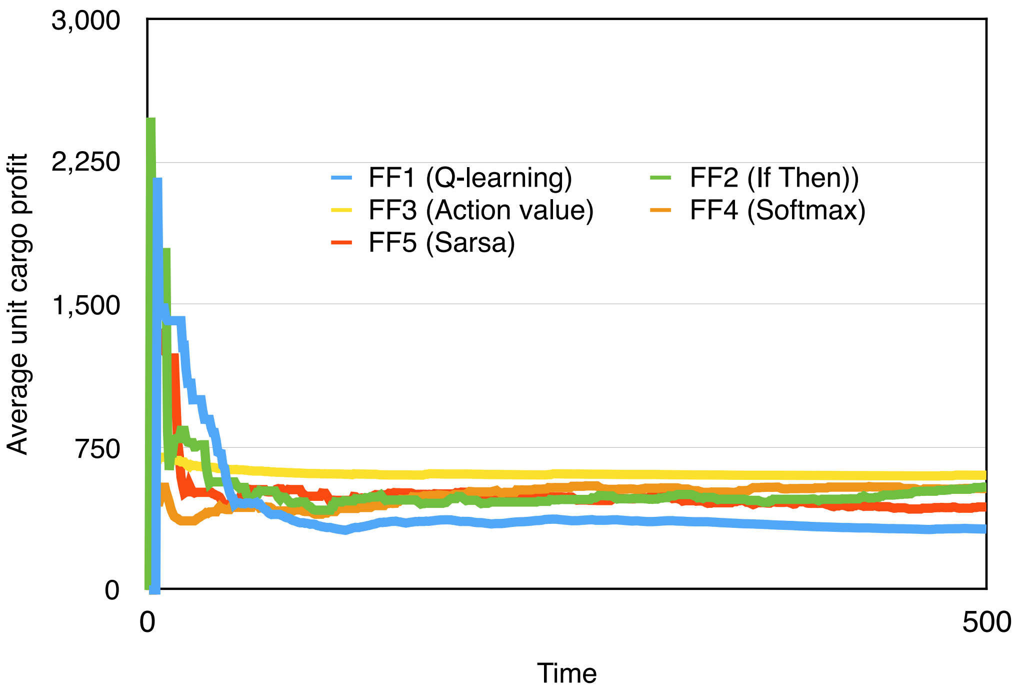

Fig. 5.59 Average unit cargo profit

For a given market, more FFs entering the market intensify the competition in the market: it drives down the total profit earned by each FF as well as the general level of profitability in the market. As a result, shippers can benefit from it but FFs suffer from losing more profits. By comparing the total profit earned by each FF in Expt. 5c and Expt. 5d (Table 5.16), we notice that the highest total profit earned by a single FF in Expt. 5c is higher than that earned in Expt. 5d. The total profit at the market level (sum of total profit earned by each FF) in Expt. 5c is also higher than that in Expt. 5d.

However, although new FFs entering a market drives down the level of unit cargo revenue (Table 5.17), unit cargo cost for each FF (Table 5.18), the combination effect of unit cargo revenue and unit cargo cost drives down unit cargo profitability for each FF in the market (Table 5.19).

Table 5.16 Total profit earned by FF agents (Expt. 5c vs. 5d)

Expt.	Total profit earned by each FF					Total profit at market level
	FF_1 (Q-learning)	FF_2 (If then)	FF_3 (Action value)	FF_4 (Softmax)	FF_5 (Sarsa)	
5c	205175260.47	91416577.46	NA	NA	NA	296591837.93
5d	34853131.01	15720746.80	11766195.84	12660231.41	17349357.89	92349662.95

Table 5.17 Average unit cargo revenue (Expt. 5c vs. 5d)

Expt.	Average unit cargo revenue					Average unit cargo revenue in the market
	FF (Q-learning)	FF2 (If then)	FF3 (Action value)	FF4 (Softmax)	FF5 (Sarsa)	
5c	1548.94	1453.52	NA	NA	NA	1517.31
5d	822.75	984.07	958.11	905.70	902.88	886.45

Table 5.18 Average unit cargo cost (Expt. 5c vs. 5d)

Expt.	Average unit cargo cost					Average unit cargo profit in the market
	FF1 (Q-learning)	FF2 (If then)	FF3 (Action value)	FF4 (Softmax)	FF5 (Sarsa)	
5c	637.2	634.32	NA	NA	NA	636.25
5d	579.92	625.08	672.35	630.5	626.32	612.60

Table 5.19 Average unit cargo profit (Expt. 5c vs. 5d)

Expt.	Average unit cargo profit of each FF					Average unit cargo profit in the market
	FF_1 (Q-learning)	FF_2 (If then)	FF_3 (Action value)	FF_4 (Softmax)	FF_5 (Sarsa)	
5c	911.74	819.20	NA	NA	NA	881.07
5d	242.83	358.99	285.76	275.20	276.56	273.85

Shipper and carrier all benefit from more FFs entering a market: more FFs improves the processing efficiency of the market. By examining the variation of demand and supply in the market (Fig. 5.60), undersupply in the market is less likely to happen although the nature of demand and supply remain unchanged as Expt. 5c (Fig. 5.26). It means most of the time, there is enough capacity to serve the demand of cargo movement, and thus shorter waiting/processing time is expected for shippers and carriers. In terms of shippers, it takes less time for a shipper to confirm a FF and have all its cargo transported from the origin to the destination. The demand of cargo movement can thus be dealt with in an efficient and timely manner. In terms of carriers, it takes less time for a carrier to fill its slots. Meanwhile, the carrier is able to move more cargo for each voyage, and thus its space can be much more fully utilized.

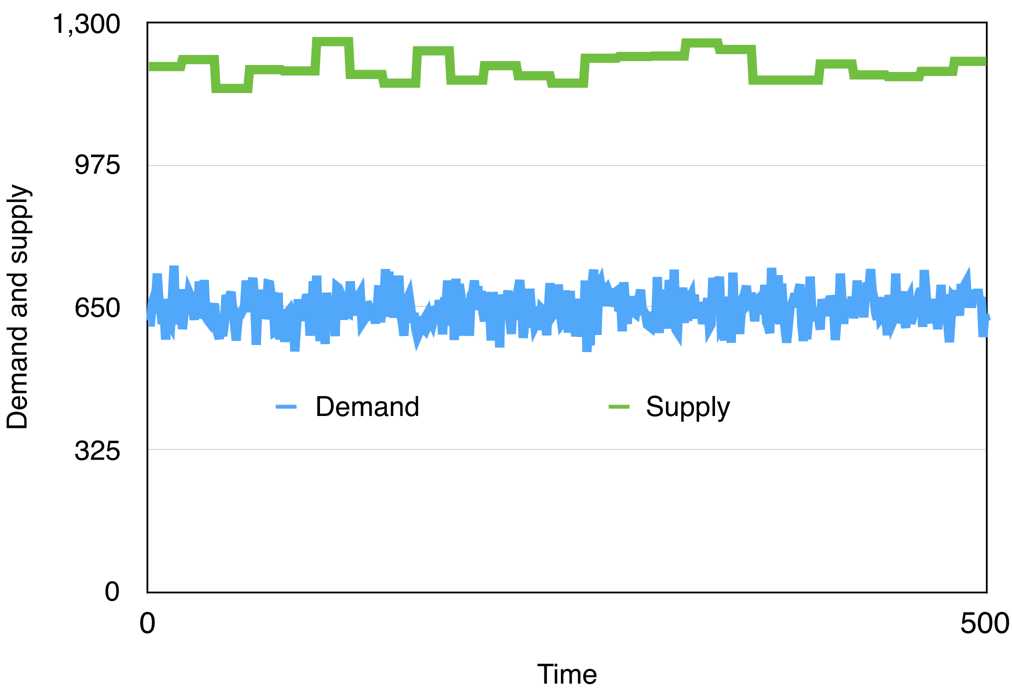

Fig. 5.60 Variation of demand and supply

CHAPTER 6 CONCLUSION

Rather than merely reducing operation cost, maximizing revenue, or achieving some form of system optimality, this study offers a new perspective to assist FFs in their pricing decisions, which takes into account: 1) the potential competitive reaction of each party, including competing FFs; 2) the decentralized manner of decision making in the logistics market; 3) learning through feedback from previous transactions; and 4) the interactive nature of the logistics market. Pricing decisions are no longer one time decisions for FFs, but are decisions adapted over iterated transactions.

In the first phase of this research, a GT approach is proposed to formulate pricing decisions for a FF when the FF has full information of the entire system. The GT approach takes into account the competition among FFs and the price sensitivity of shippers. The decision of each party is considered in a decentralized manner by incorporating the potential reaction of other interacting parties. Numerical experiments were conducted with a set of hypothetical values for key parameters – demand and price sensitivity of shippers, and the charging scheme and capacity of carriers. The results of these experiments are examined by analyzing various performance indicators (e.g. unit price, unit cost, markup etc.), and the conclusions drawn will be useful in providing insights for FF pricing decisions under competition. In order to achieve better profitability, it is suggested that FFs price segment their clients because a change in shippers' price sensitivity leads to a different optimal pricing decision. The pricing decisions by FFs should be profit-driven rather than cost-driven - they should price their services to maximize total profit by balancing price, cost and volume rather than merely trying to increase revenue/market share or lower cost. They should also formulate charges with respect to level of demand and behavior patterns of shippers/carriers rather than using the same markup across all pricing situations.

However, the pricing decisions derived using the GT approach is determined by shippers' utility functions as well as carriers' behavior patterns. Although a FF can quantify shippers' price sensitivity and probe carriers' behaviors by evaluating previous transactions or conducting surveys, the results would have to be treated with a fair amount of scepticism due to other parties' unwillingness to reveal information. Real data has not been used to test the GT model. In the numerical experiments, only sceneries with two actors in each tier were examined. Experiments on a larger scale and with multiple players in each tier have not been conducted on yet.

In the second phase of this research, learning approaches are proposed to help FFs with their pricing decisions when the FF only has limited information of the entire system. A multi-agent system is built to investigate whether learning from previous transactions can lead to better freight pricing decisions. By examining the effect of various key factors (e.g. number of iterations, shippers' price sensitivity, the size of FFs' action space, the setting of learning parameters, and level of information) on the optimal pricing decisions for FFs, this research sheds light on how good pricing decisions can be made by learning from previous transactions. The simulation results show that learning can improve the pricing performance of FFs but we still need to pay attention to the key factors mentioned above. These factors have been shown to affect the performance of learning FFs under competition.

In the third phase of the research, learning approaches proposed in Chapter 4 are modified to to help a FF formulate its best pricing decisions based on the information that is accessible to him in the real world operations. All the information the FF uses to update its pricing decision can be obtained by the FF in real world operations. We also examined the scenarios when: 1) the demand and supply are allowed to vary; 2) activities and events can occur at any time point; 3) more shippers, FFs, and carriers enter the market. The simulation results also give several practical insights into a FF’s real world operation. The multi-agent system built in this research can also be extended to examine the interaction of other combinations of shippers, FFs, and carriers as well as to test the performance of other learning models or pricing decision making models.

However, each multi-agent simulation experiment was run with a fixed setting of learning parameters for FFs that learn, although an attempt was made to determine the best parameter settings using an extensive search. It may be better for learning FFs to explore more in the beginning by adjusting the learning model parameters, and then switch over to exploitation. The limitations described above will call for further research and study. First, the proposed models should be applied in real world scenarios so that the effectiveness of each model can be improved. Second, larger scale experiments should be conducted so that more practical and meaningful insights into the pricing models developed in the research can be offered.

REFERENCES

AllBusiness. (2015). pricing decisions. from http://www.allbusiness.com/glossaries/pricing-decisions/4945494-1.html

Amaruchkul, K., & Lorchirachoonkul, V. (2011). Air-cargo capacity allocation for multiple freight forwarders. Transportation Research Part E: Logistics and Transportation Review, 47(1), 30-40.

Azadian, F., Murat, A. E., & Chinnam, R. B. (2012). Dynamic routing of time-sensitive air cargo using real-time information. Transportation Research Part E: Logistics and Transportation Review, 48(1), 355-372.

Ben-Akiva, M., & Lerman, S. R. (1985). Discrete choice analysis: theory and application to travel demand. Cambridge, Mass. : MIT Press.

Bock, S. (2010). Real-time control of freight forwarder transportation networks by integrating multimodal transport chains. European Journal of Operational Research, 200(3), 733-746.

Borshchev, A. (2013). The big book of simulation modeling: multimethod modeling with AnyLogic 6. United States: AnyLogic North America.

Brookes, M., & Altinay, L. (2011). Franchise partner selection: Perspectives of franchisors and franchisees. Journal of Services Marketing, 25(5), 336-348.

Burkovskis, R. (2008). Efficiency of freight forwarder's participation in the process of transportation. Transport, 23(3), 208-213.

Chan, C. K., Chow, H. K. H., So, S. K. P., & Chan, H. C. B. (2012). Agent-based flight planning system for enhancing the competitiveness of the air cargo industry. Expert Systems with Applications, 39(13), 11325-11334.

Chen, B., & Cheng, H. H. (2010). A review of the applications of agent technology in traffic and transportation systems. IEEE Transactions on Intelligent Transportation Systems, 11(2), 485-497.

Cheng, Y. H., & Yeh, C. Y. (2007). Core competencies and sustainable competitive advantage in air-cargo forwarding: Evidence from Taiwan. Transportation Journal, 46(3), 5-21.

Cheung, R. K., & Hang, D. D. (2003). Multi-attribute label matching algorithms for vehicle routing problems with time windows and backhauls. IIE Transactions (Institute of Industrial Engineers), 35(3), 191-205.

Chi, J., & Koo, W. W. (2009). Carriers' pricing behaviors in the United States airline industry. Transportation Research Part E: Logistics and Transportation Review, 45(5), 710-724. doi: http://dx.doi.org/10.1016/j.tre.2009.04.009

Creazza, A., Dallari, F., & Melacini, M. (2010). Evaluating logistics network configurations for a global supply chain. Supply Chain Management, 15(2), 154-164.

Ducruet, C., & van der Horst, M. (2009). Transport integration at european ports: Measuring the role and position of intermediaries. European Journal of Transport and Infrastructure Research, 9(2), 121-142.

Ertel, W. (2011). Introduction to artificial intelligence. London: Springer.

Feo, M., Espino, R., & García, L. (2011). An stated preference analysis of Spanish freight forwarders modal choice on the south-west Europe Motorway of the Sea. Transport Policy, 18(1), 60-67.

Fox, M. S., Barbuceanu, M., & Teigen, R. (2000). Agent-Oriented Supply-Chain Management. The International Journal of Flexible Manufacturing Systems, 12, 165-188.

Gardiner, J., Humphreys, I., & Ison, S. (2005). Freighter operators' choice of airport: A three-stage process. Transport Reviews, 25(1), 85-102.

Geckil, I., & Anderson, P. (2010). Applied game theory and strategic behavior. London: Chapman & Hall.

Govindu, R., & Chinnam, R. B. (2007). MASCF: A generic process-centered methodological framework for analysis and design of multi-agent supply chain systems. Computers and Industrial Engineering, 53(4), 584-609.

Groznik, A., & Heese, H. S. (2010). Supply chain interactions due to store-brand introductions: The impact of retail competition. European Journal of Operational Research, 203(3), 575-582.

Han, Q., & Timmermans, H. (2006) Interactive learning in transportation networks with uncertainty, bounded rationality, and strategic choice behavior: Quantal response model. (pp. 27-34).

Hargreaves-Heap, S. P., & Varoufakis, Y. (2004). Game theory: A critical introduction. London: Taylor & Francis e-library.

Hillier, F. S. (2010). Introduction to operations research New York McGraw-Hill.

Hirashima, Y. (2011). A new reinforcement learning method for train marshaling based on the transfer distance of locomotive.

Hiroshima, Y. (2012). On reinforcement learning methods for generating train marshaling plan considering group layout of freight cars. IAENG International Journal of Computer Science, 39(3), 239-245.

Huang, K., & Chi, W. (2007). A Lagrangian relaxation based heuristic for the consolidation problem of airfreight forwarders. Transportation Research Part C: Emerging Technologies, 15(4), 235-245.

Ip, W. H., Huang, M., Yung, K. L., & Wang, D. (2003). Genetic algorithm solution for a risk-based partner selection problem in a virtual enterprise. Computers and Operations Research, 30(2), 213-231.

Jaržemskis, A. (2005). The model of allotments booking in a shuttle train. Transport, 20(6), 236-239.

Kelly, A. (2003). Decision making using game theory: an introduction for managers. Cambridge: Cambridge University Press.

Krajewska, M. A., & Kopfer, H. (2006). Collaborating freight forwarding enterprises: Request allocation and profit sharing. OR Spectrum, 28(3), 301-317.

Krajewska, M. A., & Kopfer, H. (2009). Transportation planning in freight forwarding companies. Tabu search algorithm for the integrated operational transportation planning problem. European Journal of Operational Research, 197(2), 741-751.

Lee, J. H., & Kim, C. O. (2008). Multi-agent systems applications in manufacturing systems and supply chain management: A review paper. International Journal of Production Research, 46(1), 233-265.

Leng, M., & Parlar, M. (2005). Game theoretic applications in supply chain management: A review. INFOR, 43(3), 187-220.

Leung, L. C., Van Hui, Y., Wang, Y., & Chen, G. (2009). A 0-1 LP model for the integration and consolidation of air cargo shipments. Operations Research, 57(2), 402-412.

Li, J., & Chan, F. T. S. (2013). An agent-based model of supply chains with dynamic structures. Applied Mathematical Modelling, 37(7), 5403-5413.

Li, J., & Wang, Y. (2010). Supplier competition in decentralized assembly systems with price-sensitive and uncertain demand. Manufacturing and Service Operations Management, 12(1), 93-101.

Li, Y., Tao, Y., & Wang, F. (2009). A compromised large-scale neighborhood search heuristic for capacitated air cargo loading planning. European Journal of Operational Research, 199(2), 553-560.

Li, Z., Bookbinder, J. H., & Elhedhli, S. (2012). Optimal shipment decisions for an airfreight forwarder: Formulation and solution methods. Transportation Research Part C: Emerging Technologies, 21(1), 17-30.

Li, Z., & Hensher, D. (2012). Accommodating Risk Attitudes in Freight Transport Behaviour Research. Transport Reviews, 32(2), 221-239.

Liang, G. S., Chou, T. Y., & Kan, S. F. (2006). Applying fuzzy quality function deployment to identify service management requirements for an ocean freight forwarder. Total Quality Management and Business Excellence, 17(5), 539-554.

Liang, W. Y., & Huang, C. C. (2006). Agent-based demand forecast in multi-echelon supply chain. Decision Support Systems, 42(1), 390-407.

Lin, W. C., & Liang, G. S. (2011). Applying fuzzy zot to explore the customer service quality to the ocean freight forwarder industry in emerging Taiwan market. Research Journal of Business Management, 5(2), 77-88.

Liu, J., Yu, J., & Niu, H. (2009). An approach on carrier selection in various sections for intermodal forwarding freight agent and behavior game analysis.

Lu, C. S., & Marlow, P. (1999). Strategic groups in Taiwanese liner shipping. Maritime Policy and Management, 26(1), 1-26.

Lu, J. C., Tsao, Y. C., Charoensiriwath, C., & Dong, M. (2012). Dynamic decision-making in a two-stage supply chain with repeated transactions. International Journal of Production Economics, 137(2), 211-225.

Lun, Y. H. V., Lai, K. H., & Cheng, T. C. E. (2010). Shipping and Logistics Management. New York: Springer London Dordrecht Heidelberg.

Mankiw, N. G. (2012). Principles of economics Mason, OH South-Western Cengage Learning.

Markides, V., & Holweg, M. (2006). On the diversification of international freight forwarders: A UK perspective. International Journal of Physical Distribution and Logistics Management, 36(5), 336-359.

Matlab. (2015). Optimisation Toolbox - Nonlinear Equation Solving. from http://www.mathworks.com/products/optimization/features.html#nonlinear-least-squares%2C-data-fitting%2C-and-nonlinear-equations

Moccia, L., Cordeau, J. F., Laporte, G., Ropke, S., & Valentini, M. P. (2011). Modeling and solving a multimodal transportation problem with flexible-time and scheduled services. Networks, 57(1), 53-68.

Mostafa, T. S., & Talaat, H. (2010). An Intelligent Geographical Information System for Vehicle Routing (IGIS-VR): A modeling framework.

Mozafari, M., & Karimi, B. (2011). Pricing for freight carriers in a competitive environment: A game theory approach. International Journal of Industrial Engineering Computations, 2(3), 467-478. doi: 10.5267/j.ijiec.2011.04.004

Mutlu, F., & Çetinkaya, S. (2013). Pricing decisions in a carrier–retailer channel under price-sensitive demand and contract-carriage with common-carriage option. Transportation Research Part E: Logistics and Transportation Review, 51, 28-40. doi: http://dx.doi.org/10.1016/j.tre.2012.12.003

Nagle, T. T., Hogan, J. E., & Zale, J. (2011). The strategy and tactics of pricing: a guide to growing more profitably. Boston: Prentice Hall.

Ni, D., & Li, K. W. (2012). A game-theoretic analysis of social responsibility conduct in two-echelon supply chains. International Journal of Production Economics, 138(2), 303-313.

Pan, A., & Choi, T. M. (2013). An agent-based negotiation model on price and delivery date in a fashion supply chain. Annals of Operations Research, 1-29.

Pidduck, A. B. (2006). Issues in supplier partner selection. Journal of Enterprise Information Management, 19(3), 262-276.

Rau, H., Tsai, M. H., Chen, C. W., & Shiang, W. J. (2006). Learning-based automated negotiation between shipper and forwarder. Computers and Industrial Engineering, 51(3), 464-481.

Reinheimer, S., & Bodendorf, F. (1999). A framework for electronic coordination in the air cargo market. Information Society, 15(1), 51-55.

Russel, S. J., & Norvig, P. (2010). Artificial intelligence: a modern approach. Upper Saddle River, N.J. : Prentice Hall.

Saeed, N. (2012). Cooperation among freight forwarders: Mode choice and intermodal freight transport. Research in Transportation Economics.

Schindler, R. (2012). Pricing strategies: a marketing approach. Thousand Oaks, Calif: Sage Publications.

Shiau, T. A., Lin, L. M., Ding, J. F., & Chou, C. C. (2011). Hub location selection of third-party logistics service on multiple countries consolidations for ocean freight forwarders by using fuzzy multiple criteria decisionmaking (MCDM) approach. International Journal of Physical Sciences, 6(19), 4548-4557.

Shum, P. C. C., & Ng, V. T. Y. (2010). Multi-site collaboration design for air cargo planning.

Simongáti, G. (2010). Multi-criteria decision making support tool for freight integrators: Selecting the most sustainable alternative. Transport, 25(1), 89-97.

Smith, T. J. (2012). Pricing strategy: setting price levels, managing price discounts, & establishing price structures. Mason, Ohio: South-Western Cengage Learning.

Solesvik, M. Z., & Encheva, S. (2010). Partner selection for interfirm collaboration in ship design. Industrial Management and Data Systems, 110(5), 701-717.

Sutton, R. S., & Barto, A. G. (1998). Reinforcement learning: an introduction. Cambridge, Mass.: MIT Press,.

Swaminathan, J. M., Smith, S. F., & Sadeh, N. M. (1998). Modeling Supply Chain Dynamics: A Multiagent Approach. Decision Sciences, 29(3), 607-632.

Taha, H. A. (2007). Operations research: an introduction Upper Saddle River, N.J. : Pearson/Prentice Hall.

Tongzon, J. L. (2009). Port choice and freight forwarders. Transportation Research Part E: Logistics and Transportation Review, 45(1), 186-195.

Toptal, A., & Bingöl, S. O. (2011). Transportation pricing of a truckload carrier. European Journal of Operational Research, 214(3), 559-567. doi: http://dx.doi.org/10.1016/j.ejor.2011.05.005

Uster, H., & Agrahari, H. (2010). An integrated load-planning problem with intermediate consolidated truckload assignments. IIE Transactions (Institute of Industrial Engineers), 42(7), 490-513.

Wen, C. H., Tsai, M. C., & Lin, C. H. (2011). Classification and competition analysis of air cargo logistics providers: The case of Taiwan's high-technology industry. Journal of Air Transport Management, 17(2), 106-109.

Wong, W. H., Leung, L. C., & Hui, Y. V. (2009). Airfreight forwarder shipment planning: A mixed 0-1 model and managerial issues in the integration and consolidation of shipments. European Journal of Operational Research, 193(1), 86-97.

Wooldridge, M. (2002). An Introduction to Multiagent Systems. Chichester, England: John Wiley & Sons.

Wu, C. H. (2012). Price and service competition between new and remanufactured products in a two-echelon supply chain. International Journal of Production Economics, 140(1), 496-507.

Xiao, F., & Yang, H. (2007). Three-player game-theoretic model over a freight transportation network. Transportation Research Part C: Emerging Technologies, 15(4), 209-217.

Xu, L., Bu, X. Z., & Tian, L. W. (2010). Study on marine shipping contract allocation and pricing policy on shipper's Loss Aversion. Paper presented at the Proceedings - 2010 International Conference on Service Science, ICSS 2010.

Yang, C. C. (2012). Assessing the moderating effect of innovation capability on the relationship between logistics service capability and firm performance for ocean freight forwarders. International Journal of Logistics Research and Applications, 15(1), 53-69.

Yin, M., & Kim, K. H. (2012). Quantity discount pricing for container transportation services by shipping lines. Computers and Industrial Engineering, 63(1), 313-322.

Zhang, D. Z., Anosike, A. I., Lim, M. K., & Akanle, O. M. (2006). An agent-based approach for e-manufacturing and supply chain integration. Computers and Industrial Engineering, 51(2), 343-360.