

Transport On-Demand in a Service Supply Chain Experiencing Seasonal Demand: Managing Persistent Backlogs

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Abstract: Successful transport-on-demand (TOD) requires having sufficient capacity in the right location to meet demand when it occurs. Consumer and recovery vehicle locations are variable, and the vehicle recovery service is contracted out in the service supply chain. This research aims to identify how different variables/factors influence backlogs during busy periods and service performance. A case study of a vehicle recovery company was undertaken using observation and analysis of historical data to map the process. Discrete event simulation (DES) was used to model several processes to evaluate the operational impact of changes. We find that ensuring complete and accurate information transmission over the chain supports the TOD service by enhancing the ‘allocation’ activity of the dispatch center staff; i.e., pairing vehicles to consumer requirements. Simple changes to how information is collected, shared, and used in the service supply chain can significantly reduce the percentage of jobs taking more than a given time.

Keyword — transport-on-demand (TOD), vehicle recovery service provider (VRSP) backlog, service supply chain, information accuracy, information completeness.

1. INTRODUCTION

The planning of logistics capacity to meet demand is a well-recognized problem that has spawned a significant body of research over the years. However, much of this research is predicated on the premise that the demand factors remain largely unchanged or are known in advance. When this is the case, planning to meet demand becomes a relatively simple problem. However, there exist categories of logistics exercises where the service provider must meet demand as it occurs, unknown in advance, while also being able to satisfy this demand promptly; this is a transport-on-demand (TOD) system.

Within such a TOD system, there are two key approaches that could be used to meet demand. First, providing an abundance of capacity ensuring that there is always logistics capacity available to meet demand when and where it occurs. However, capacity is not always affordable relative to the potential to earn revenue. Also, the cost of capacity can often increase at a rate faster than revenues might rise. Under the circumstances, merely adding capacity to meet demand is probably going to be an insufficient outcome.

Second, simply allowing the customers to wait in a queue until there is sufficient capacity to meet their demand. While queuing may be acceptable in some industries, we are concerned with a TOD situation with a requirement to be “on time.” When timeliness of responses built into a specific key performance indicator (KPI), managing a backlog of customers becomes unacceptable.

In this research, we explore real-world service supply chain where there are persistent backlogs experienced by the vehicle recovery service provider (VRSP) that provides transport on demand, fulfilling the service promise of the service provider to the customer or consumer of the service (Demirkan & Cheng, 2008). The VRSP contracts out their logistics capabilities to a service organization who on-sells these services as part of a package to their consumers. In the subcontracting relationship, while costs have increased significantly there remains a limited

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opportunity to improve revenue, forcing the VRSP to explore other methods of enabling them to deliver the services required and meet their performance KPIs.

This research is motivated by the experience of ‘persistent backlogs’ at a vehicle recovery service company contracted to provide transport on demand (TOD). Surges in demand due to seasonality detrimentally impacted the logistics performance, and this remains poor over an extended period, effectively multiplying the impact on the KPI. The focus of this research is to understand the dynamics of the system to identify particular variables that can be controlled to reduce the incidence or severity of backlogs. When a backlog of work occurs, there is a delay propagation where the jobs received in the near-future are also likely to become backlogged. As a result, when there are on-demand requirements and efficiency-focused KPIs, a period of high demand/congestion will have a disproportionate impact on the efficiency KPIs beyond the initial congestion period.

This research is important as there is limited literature on the practice of management of TOD problems, in comparison to modeling work that addresses these problems. This research did not aim to develop theories. Instead, the purpose was to resolve problems regarding persistent backlogs at the VRSP and to propose and test methods that could be used in practice to address the problem. Therefore, in contrast with how to route vehicles under the TOD problem (e.g., as in modeling research), we investigate process and supply chain factors that can be remedied to reduce the severity of backlogs. While the problems investigated (e.g., the dial-a-ride problem (DARP) (Coslovich et al., 2006) and ambulance relocation (Gendreau et al., 2001)) share similarities with our work, the key difference lies in the positioning of the logistics infrastructure and constraints on capacity use. We examine a case where demand and supply are dynamic in space, the capacity of the vehicles is heterogeneous, and the transport is provided by a vehicle recovery service provider in a service supply chain where the flow of information can impact service performance (Breibach et al., 2015).

The rest of the paper is structured as follows. First, we review a range of literature pertinent to the problem at hand. Second, we discuss the observational data collection approaches that were used followed by an overview of the simulation modeling approach that provided indications of effective solutions focused on the allocation activity in the process. Third, we present our results with a focus on historical patterns and correlations – and the developed understanding of how performance could be improved within the real-world constraints of the vehicle recovery service providers.

2. LITERATURE REVIEW

Increasingly, firms turn to outsourcing arrangements as they seek improved performance. There is increasing reliance on resources and capabilities from partners in a wider network, associated with the performance of the service in question (Lin et al., 2012). Partnering enables firms to tap into additional capabilities and focus on their core competencies. While manufacturing outsourcing has been well-examined, despite the plethora of opportunities to outsource services, the service outsourcing literature still lags practice. This situation is exacerbated by the fact that it is not always possible to simply ‘adopt’ a proven strategy from manufacturing when managing a service operation. Thus, while many operations management and control concepts can be transferred directly from manufacturing directly to service management, simply doing this without also considering changes to capacity in services is fraught with challenges (Anderson et al., 2005). Within services, capacity is often flexible and must be adjusted to meet fluctuating demand levels, particularly as firms struggle to satisfy customers that must be queued – unserved – until there is appropriate capacity ready. Such problems plague customer-facing services and have been well-documented in healthcare services, with solutions often focusing on buffer management to improve customer service (Umble and Umble, 2006).

In manufacturing environments, managers can hold additional inventory to ‘protect’ themselves peaks in seasonal demand. In services, however, the output cannot be stored; to maintain service delivery performance in the face of demand fluctuations different approaches are required. These approaches concern the current situation (i.e., AS-IS model) as well as the desired situation (i.e., TO-BE model) and the transformation path to move from the AS-IS model to the TO-BE model (Chen et al., 2008).

Service vendors’ resources can be ‘consumed’ for extended periods during peak events, preventing that resource from attending to other work. The extended need for the resources lays the groundwork for circumstances where the system does not recover when the peak period of demand finishes; the backlog can take significant time to reduce and is, therefore, a ‘persistent backlog.’ When using traditional KPIs (e.g., 90% success in processing a customer in a certain period), the dependence of subsequent jobs on the current (lagged) job becomes important. Firms acting within supply chains can find this problem compounded, as may lack freedom of flexibility while being required to adhere to strict service-level agreements (SLAs).

The difficulties in building a schedule that is robust on delay propagation have been an increasing focus of public transport scheduling (Caprara et al., 2014; Corman et al., 2014). Here, both the demand and resources are relatively fixed, but the focus has increasingly turned to the impact on future services of a disruption to current

services; recognizing the ‘knock-on’ effect that can be created during scheduling. In these circumstances, there are no difficulties relating to the transmission of information over a supply chain, impacting the services.

2.1 Transport On-Demand

The growing emphasis on just-in-time deliveries and the compression of cycle times over the supply chain have motivated increased research into the TOD problem (Cordeau et al., 2007). While such TOD systems require consideration of three key tasks (viz., clustering of customer jobs to gain economies of scale, vehicle routing to reduce transportation costs, and scheduling to ensure satisfaction), a vehicle recovery service is a very specific dynamic TOD problem, with an emphasis on the locational issues and the inability to reject work.

In a vehicle recovery case, the subcontractor is unable to reject work and must accept the job; this is in contrast to some DARP problems as examined in Coslovich et al. (2006). Given the relatively constant nature of the demand on the system, it is challenging to implement a ‘rank-homing’ heuristic (e.g., as explored in Horn (2002)) to rebalance the location of vehicles. The nature of the work requires that one job is completed before another begins, and so it is not possible to cluster customer jobs. In this TOD problem, the use of capacity tends to be reactive to the emerging situation and customer requirements. This reactivity means that methods such as territory planning (Zhong et al., 2007) or developing a daily master schedule (Sungur et al., 2010), allowing various vehicles to share capacity, are both inappropriate as resolutions to the problem.

2.1.1 Extraneous factors impacting TOD performance in a service supply chain

Planning for stochastic demand with a fixed logistics resource ensures that a relatively high service level is met close by to the fixed resources. The problem becomes more challenging as resources can be mobile but tend to be closer to the fixed station.

With TOD activities, there are many extraneous factors that firms must be aware of and manage carefully; e.g., traffic congestion (Sankaran and Wood, 2007) and partnering with firms that possess complementary capabilities (Breidbach et al., 2015). Therefore, managers’ ability to focus on a narrow set of most relevant variables means that a large set of variables must be reduced to those that are most pertinent. The reduction enables improved managerial oversight on core variables. Control processes based on backlogs tend to be robust (Powell et al., 2001). However, robust policies to manage capacity while maximizing profit, within a set of worst-case scenarios, still need further attention.

2.2 Service Supply Chain and Information Flow

This research is motivated by a situation where both the recovery vehicles themselves as well as the demand locations vary under these circumstances, it is often difficult for a vehicle recovery service provider to maintain services delivered within a particular period, as it is difficult to plan where the vehicles will be positioned at any particular point. Therefore, planning for capacity to match or exceed demand becomes a significant challenge.

Service supply chains consist of a bidirectional flow of information and include a customer or consumer, a service retailer that interfaces with the consumer, and a provider of the service activity itself (Sampson, 2000). In this way, there is a provider of infrastructure, the retailer, and the customer (Demirkan & Cheng, 2008). In some service supply chains, the situation will come about where a client firm interacts directly with the consumer and then subcontracts out the performance of the actual logistics operation to the vehicle recovery service provider (Figure 1). Under these circumstances, there is a flow of information between the consumer (e.g., location and requirements) to the ClientFirm (i.e., they are a retailer of the service that interfaces with the consumer) whose call center then passes the information through to the VRSP, charged with providing the vehicle recovery service to the consumer (i.e., they provide the service infrastructure and undertaken the activities associated with the service delivery). In this way, the service supply chain falls into the bidirectional category, where the consumer provides information as an input into the service and in return be the beneficiary of the final service (Sampson, 2000). The flow of information underpins the success of the integration (Gustin et al., 1995).

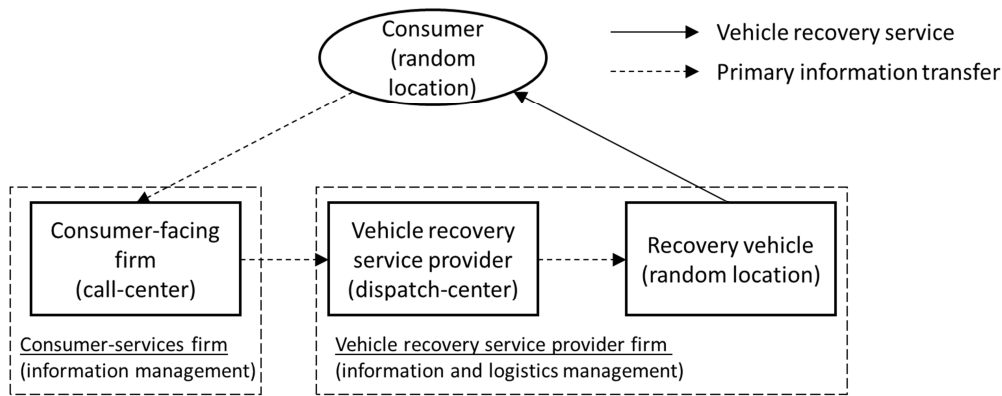


Figure 1. Service supply chain case where the vehicle recovery service is subcontracted to a vehicle recovery service provider firm by the consumer-facing (consumer-services) firm.

An additional difficulty comes from the fact that the vehicles are constantly shifting. Operational planning cannot proceed by assuming a given resource at a certain point in the future. A given job may take a resource quite a distance from the starting point; even if a network were established initially with vehicles spread over a region, there would need to be constant – and expensive – rescheduling of resources to enable a persistent coverage. The use of dynamic policies can provide advantage where useful information is available as early as possible (Mitra, 2013).

2.3 Key Performance Indicators in Call Centers

In the services supply chain to deliver TOD, capturing full and complete information about the consumer and requirements at the first stage is crucial to ensuring the service can be delivered appropriately. There are several commonly applied operational performance indicators in call centers, all easily implemented and monitored with automatic records (Hasija et al., 2008; Jaiswal, 2008):

- **Adherence** is the percentage of time the call center agent is available for call work relative to their total time that they are scheduled to be available.
- **Abandonment Rate** is the ratio of the number of calls abandoned by the customer before answering to the number of calls made to the call center.
- **Average Talk Time (ATT) or pay-per-time (PPT)** (when outsourcing) measures the average time of a customer is connected to an agent in a call.
- **Pay-per-call (PPC)** (when outsourcing) is the measure of call center performance based on the number of customers served.
- **Pay-per-resolution (PPR)** (when outsourcing) is the resolution rate of first calls served. The resolution indicates that the core problem is solved, and no further query is required.

While most of these operational measures remain prevalent in the evaluation of ‘efficiency’ measures (e.g., focused on cost reduction or maintaining a low-cost operation), they are less useful as customer-focused metrics and may not drive customer-focused outcomes. Among these methods, the PPR metric focuses most on a customer-focused outcome.

There is a further impact on the upstream firm; the KPIs set there can significantly impact on the ability to secure appropriate types of information in support of downstream firms (sub-contractor) who provides the logistic service to the consumer.

The call center KPIs of both parties should be aligned and support the provision of accurate and complete information along the service supply chain. Effective vehicle recovery service requires accurate and complete information from the consumer – through the upstream firm – to accomplish this task. The simultaneity characteristics of this service (i.e., the provision of service only occurs when the service provider and the service customer are both present in the service environment) reinforce the necessity for complete and accurate information to ensure the service quality (Cho et al., 2012).

If efficiency focused call center KPIs (e.g., ATT) are used in an upstream call center, to maintain cost advantages (Jaiswal, 2008), the behavior of call center agents would be influenced to finish calls quickly. In contrast, they may become less concerned with securing complete and accurate information. If this occurred in a given case, the service quality might be negatively impacted.

In a single organization, ATT has been criticized for the way that it influences the delivery of poor service quality in practice (Feinberg et al., 2000; Rafaeli et al., 2008). Customer Orientation Behaviors (COB) are the “employee behaviors that indicate an interest in serving customers but are not a part of the employee’s formal job description.” (Rafaeli et al., 2008, p. 241), demonstrated two criticisms of the use of ATT. First, ATT constrains the calls’ service time relative to customers’ queries and decreases agents’ COB, which in turn lowers the service quality. Second, COB, in contrast, encourages call center agents to extract complete and accurate information from customers queries in call centers.

Over a multi-firm organization, the system-wide outcomes can deteriorate if certain sites or operations within the system attempt to maximize their goals, independent of the system. The goals of each site or operation should be integrated and coordinated into the system’s performance (Wang et al., 2015). There, appropriate KPI settings in the call center should be aligned so that behaviors of the call center staff directly support the system-wide objective of consumer satisfaction. Specifically, the KPIs of the call center should encourage quality of information obtained over the efficiency of handling customers’ queries.

2.4 Research Question

Given this background, we seek to address how the TOD-focused vehicle recovery service provider can work with their client firm to improve their on-time performance, expressed as a percentage of jobs completed within the specified timeframe.

3. METHODOLOGY

This study provides an in-depth case examining the determinants of persistent backlogs in on-demand vehicle recovery services and examines how these can be reduced. The issues faced in our case involved meeting required service levels/KPIs within the service supply chain, specifically by reducing the incidence of service backlogs. By examining this particular case, key contributors to the service backlog problem are highlighted and approaches to resolve the problems are explored in a simulation study.

A key consideration when selecting the appropriate methodology was ensuring that there was a good fit with the underlying problem. Case studies are often used to investigate existing and on-going phenomenon and can capture real-time dynamics; they are particularly useful when the boundaries between the phenomenon and the context are unclear (Yin, 2014). The case study method has been recognized as particularly useful when addressing questions that focus on ‘how’ or a ‘why’ questions. In this study, we sought to answer these questions:

1. What factors contribute to the backlogs?
2. How do these factors relate to backlogs?
3. How can management actions be taken to enable the firm to meet their KPIs?

These intentions are aligned with the explorative nature of a case study, where it is perceived to be appropriate to enable researchers to generate or test new approaches and develop a theory (Eisenhardt, 1989).

To address the research problem, we selected a specific case in the New Zealand business environment, consisting of two service organizations serving consumers (Figure 2). The first organization was ClientFirm, which interfaced with consumers and provided a range of logistics and motoring services, including support when the consumers’ vehicle breaks down. While ClientFirm had a range of in-house services, they contracted out vehicle recovery services to a range of other firms, including VRSP. When a consumer needed the vehicle recovery, the ClientFirm dispatch officers transferred the data to the second firm, the contractor (VRSP), who executed the vehicle recovery service to the consumer. To address the question of how to reduce backlogs and improve service performance, we first established the current situation (i.e., AS-IS model) based on the operational data.

VRSP struggled to maintain their KPI based on arriving at a consumer within a set time-window, a percentage of the time. While this was ordinarily achievable, the lapses were largely driven by backlogs of work during busy periods. Exploring how they can achieve this KPI (i.e., TO-BE model), therefore, became the primary driver for the research.

The data were gathered in two phases. First, we undertook a process mapping exercise. This involved collecting data from semi-structured interviews with key managerial and operational staff (primarily, VRSP’s general manager and operations manager) and collecting observational data over the process, from ClientFirm as they first interact with consumers, through to the vehicle recovery process at the consumers’ vehicles. Second, we queried historical data records, ensuring that our data was not biased by simply taking a small slice in time. (The subsequent analysis of records indicated wide variations in performance over time, validating our desire to ensure we had a representative sample of data.) Furthermore, it was decided that observing and timing participants would produce unreliable estimates of the time taken to perform each task as participants might adjust their work patterns and habits when

they observed. Therefore, we opted to use a historical dataset with data from VRSP, the ClientFirm, and the data transferred electronically between them. Statistical characteristics of gathered data are presented in Appendix 1. Together, these sources of data enabled us to work through a process mapping followed by simulation experiments.

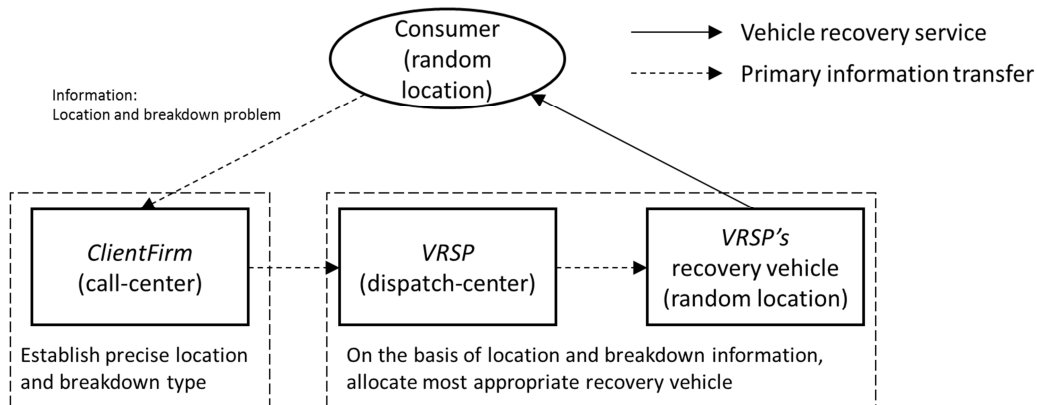


Figure 2. Primary system-wide information flows. ClientFirm collects key data from the consumer then transmits this to VRSP using EDI technology; VRSP then uses this information to allocate the most appropriate recovery vehicle.

4. RESULTS

We first present the results of the process mapping, followed by the simulation results.

4.1 Process Mapping

First, we engaged in process mapping by having members of the research team go on-site and follow the process through from the ClientFirm, to the VRSP dispatch center, and then out with VRSP drivers. The process mapping sensitized to the researchers to the key issues addressed during the process. The observations provided the research team with an overview of the system and an understanding of the complexities and dynamics that needed to be addressed.

Having observed the process, we worked to create a process map or a visual representation of what normally occurs. This is the “as is” map representing the process as is currently conducted. Initial process maps were checked with the Dispatch Manager at ClientFirm and with the Operations Manager at VRSP to ensure the map was a reasonable reflection of the core activities involved in the process. In the model, we showed the primary flow and sequence of activities, rather than attempting to capture the full complexity of the activities required over a range of related services.

We mapped the process to replicate what is currently undertaken (the “as is” model). Several opportunities for improvement were identified after observing the process and also discussing this with the staff at VRSP. The possible improvements were encoded in a “to be” process map (i.e., this map is aspirational and shows an improved process) and

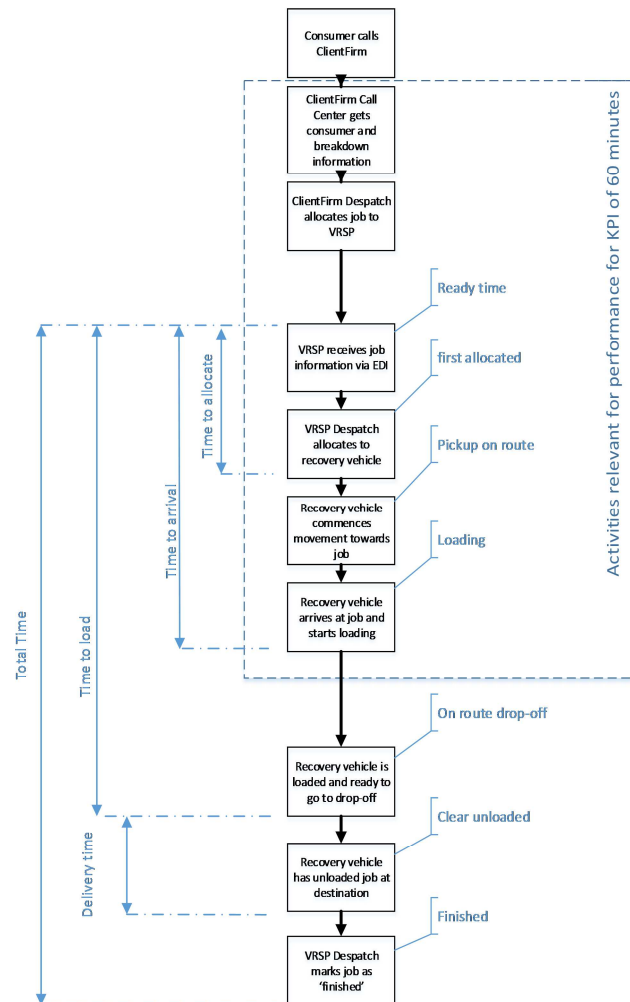


Figure 3. Major process steps and key milestones used to form the service performance KPI for LSP

created a modified process model (the “to be” model). The process consists of three major milestones (Figure 3):

Time-to-Arrival – the vehicle has arrived at the consumer location. Time-to-arrival is the primary KPI, and should be less than 60 minutes as agreement in the contract with the Client Firm (call-center)

Time-to-Load – when the vehicle has reached the consumer and has secured the consumer’s vehicle and is ready to take it to the destination

Total Time – the vehicle has retrieved the consumer vehicle, delivered it, and is ready to start the next allocated job.

A careful analysis of years of historical records indicated that many of these activities in the process were completed in a consistent period. An exception was the ‘allocation’ activity that involved the allocation of specific vehicles to a given job, ensuring that the pairing of vehicles was sufficient to resolve problems. At times, this required a re-allocation, as an initially allocated vehicle may become required elsewhere or if more information is gathered indicating that the initially allocated vehicle is insufficient to accomplish the task.

4.1.1 Determinants of service quality and information quality

When the Consumer experiences a vehicle breakdown, they call ClientFirm, and the call is taken by the ClientFirm’s call center staff. Necessary information was transferred from the call center through to the appropriate contractor (in this case, VRSP) who used this information to route a vehicle recovery truck to the consumer’s location, after that they provided a vehicle recovery service to the consumer (Figure 2). Capturing, recording, and transferring accurate and complete information assisted the effective delivery of the service by the contractor.

No two jobs were the same; the combination of consumer location and specific type of technical problem together influence the type of vehicle required. A vehicle that was broken down on the roadside may be sufficiently served with a ‘standard’ vehicle with a ‘standard’ fit-out. Other constraints, such as needing to enter a parking building, may limit the types of vehicles that can access the location (e.g., due to height restrictions). Some breakdowns made it impossible to use a ‘standard’ vehicle and they instead required a much more expensive and, therefore, uncommon vehicle. This heterogeneity makes it important to have the correct and complete information as early as possible. Furthermore, it was not a hierarchical relationship where a standard vehicle can accomplish a proportion of the jobs while a more specialized vehicle can accomplish the same jobs plus additional jobs requiring the specialist vehicle itself. Therefore, the allocation of a vehicle to the requirements of a job is a crucial activity within the process.

A further complication in the allocation decision comes from the pairing of the drivers’ skillset and capabilities with the requirements of the task. It takes time for a new hire to become proficient in all types of jobs at all levels of complexity; a given job may only require a standard vehicle, but it may need to be coupled with a more capable driver.

Specialist vehicles are often held back to ensure they are available if required for a given job. Under circumstances where a specialist vehicle is allocated to a job that doesn’t require it, this vehicle is no longer available for a new job where it is required, significantly delaying the time when it can commence movement to the next job. Having complete and correct information from the consumer ensures proper allocation of specialist vehicles.

During the observations made by the research team at the VRSP dispatch office and when with the VRSP recovery vehicles, it became clear that there are many circumstances under which additional information was required. Observations were made that VRSP staff often had additional, follow-up questions regarding job details. The follow-up resulted in additional information being requested from the consumer. When this occurred, it was ‘on the clock’ for VRSP and reduced their ability to get the vehicle to the consumer within 60 minutes. Therefore, when more time is used to secure this additional information it meant less time was available for VRSP to provide the service.

If complete information can be acquired by the ClientFirm before the information was provided to VRSP, this supported VRSP to focus on the core service and to reach the consumer with the appropriate resource within 60 minutes. However, ClientFirm’s call center staff managed and took calls on a range of issues, not just those requiring a recovery vehicle from VRSP. The variation in the in-coming call types made it difficult to understand what specialist questions would be most appropriate for any given call. Also, not all consumers were equally knowledgeable about mechanical or electrical problems their vehicle may be experiencing.

There are limits to the level of improvement in the service VRSP was able to make solely by implementing changes in their internal operational procedures. The inputs impacted the ability of VRSP to deliver the vehicle recovery service – specifically, the quality of the information received by VRSP from the ClientFirm is crucial. In general, more complete and accurate information was believed to enable VRSP to more effectively deliver the service, by directly supporting an effective allocation activity in the process.

4.1.2 Call-Center KPIs and the Service Supply Chain

Observations at the VRSP dispatch center and the VRSP vehicle recovery trucks indicated that VRSP often required updated information after the initial job was received from the ClientFirm, leading to a delay in the overall service time due to a slower allocation activity or a required re-allocation of an alternate vehicle if new specialist requirements were determined.

Like many inter-firm partnerships, a core requirement is for all parties to have the information input necessary to complete their part of the system-wide process. Collecting and recording the right information started with the first organization and their ability to secure the right and most appropriate information. The information should then be passed to the VRSP Dispatch team, allowing them to allocate effectively the VRSP resources to each job, and the information should then be passed to the VRSP recovery vehicle allocated to that job (Figure 2). Many intra- and inter-firm information sharing challenges had already been addressed by at VRSP including the use of information and communication technology (ICT), effective systems to capture information (i.e., data entry in the call center), and then sharing this information between locations, including mobile tablets in recovery vehicles.

KPIs (as mentioned in section 2.3) used at the ClientFirm call center already balanced both efficiency and effectiveness and therefore supported the call center staff in their job to elicit full information from the consumer. ClientFirm evaluated both the consumers' experience in contact with ClientFirm and also the system-wide performance resulting in the vehicle recovery service. While ClientFirm worked to capture full and complete information, they acknowledged that they are not the experts on the type of information required by VRSP. Where information was incomplete or inaccurate, the process had to stop while information was checked with the consumer. In some cases, this resulted in a re-allocation of vehicles to the consumer.

4.2 Seasonal Variation and Persistent Backlogs

A complete set of operational data relating to the performance of day-to-day activities was required to understand the current process performance in the context of historical performance. The full set of data allowed us to evaluate how a range of variables and factors are dynamically related. A full presentation of operational correlations specific to VRSP is not reported here; instead, we focus on the key elements relating to the inter-organizational supply chain that enables VRSP to provide the vehicle recovery service to the consumers. The analysis provided indications that the allocation activity at VRSP was a core activity that was highly relevant to improving the service level they provide.

Over time, several seasonal patterns emerged over the daily, weekly, and annual timeframes. Each day, there were patterns of heavy traffic during the rush hours in the mornings and evenings (i.e., as employees travel to and from their workplaces). On a weekly basis, there were heavier loads on Monday; breakdowns that occur over the weekend were picked up for delivery to the automotive garages that open Monday morning. Breakdowns on the weekend may occur a long way from home or work (e.g., at a beach) and, therefore, required a longer distance for travel (which consumes the vehicle for a longer period). Over a year, there were longer trips during summer holiday periods when consumers travel further from home (which is also when there are likely to be difficulties scheduling staff to provide capacity); vehicles travelled further to reach the consumers' vehicles and then back again to bring consumers back to the city (again, consuming vehicles for a longer period).

On a daily basis, when the peaks in seasonal demand occur during rush hour traffic periods, the vehicles remain busy for a longer period than just the seasonal peak. Where one job takes longer than expected, other jobs that occur at the same time are backlogged. This 'knock-on effect' means that the later jobs face a delayed start and then a delayed finish (Figure 4). The overall effect is that while there is a relatively short surge in demand, the impact on timely completion extends beyond just the short duration of this peak period in seasonal demand.

As poor performance in terms of timely completion therefore extended over a longer period, this resulted in a greater impact on the timely completion KPI. A busy period may impact not just the one or two jobs occurring during this period but may impact on several more jobs occurring afterward, causing all these jobs to take too long.

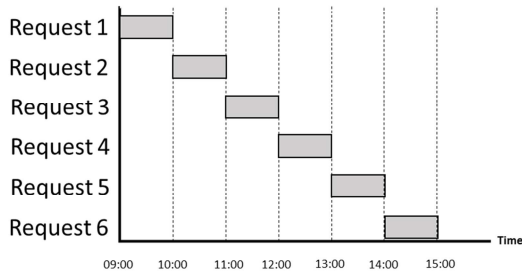
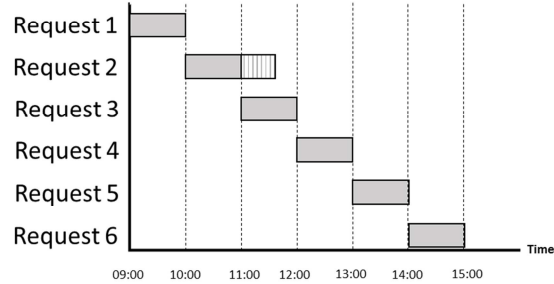
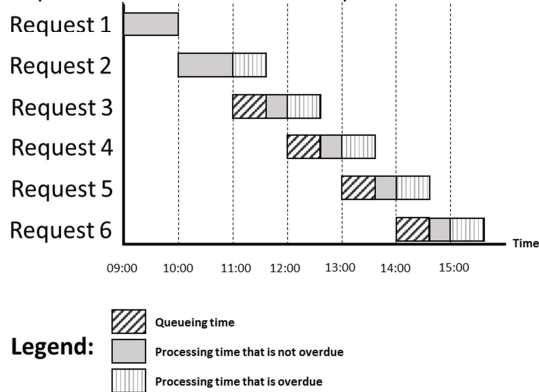
Panel A: the ideal deterministic case**Panel B: the 'mental model' that one delay has no knock-on effect****Panel C: the actual situation with repeated failures to provide service within the required timeframe**

Figure 4 The three panels represent the ideal case, what is believed to happen (i.e., the 'mental model' of managers), and the actual situation.

Panel A shows that if all jobs arrived at a consistent pace and all processing times were consistent, there would be no failures to process each job within the required timeframe.

Panel B shows the mental model of the situation, where a single request takes longer to process, marking one request that is overdue, with other jobs still being within the required timeframes.

Panel C shows the reality; a delayed job has a knock-on effect, resulting in multiple jobs now being overdue. Therefore, a single incident causes repeated jobs to go over the required processing time and this rapidly creates an adverse effect on the KPI of the percentage of jobs completed within the required timeframe. The single first job overdue (Request 2) means that the remaining requests are, even if processed in an appropriate amount of time, going to be overdue, representing a 17% completion rate that is far below the required 90% of jobs that deliver on-time service.

4.3 Discrete Event Simulation (DES)

Following the creation of the process map and an analysis of the historical data, the process was modeled in discrete event simulation (DES) software using ExtendSim. The software enabled us to draw on historical data to provide insight into how different processes were undertaken in the past. The simulation then ran a sequence of jobs (modeled on the data provided) through each of the activities in the process sequence. The results enabled us to understand how the overall behavior of the system responded to different circumstances. This model allowed us to adjust the process and experiment with changes to the process to understand how proposed changes will impact on the overall outcome. Using different simulations for the AS-IS and TO-BE process maps provided us with the opportunity to evaluate the strengths and weaknesses of these two processes. (Experimental settings for the simulation model are presented in Appendix 2.)

4.3.1 Simulation Results

We used the simulation results to evaluate the performance of process changes, using the TO-BE model. We then compared the results of TO-BE and AS-IS model to determine whether the suggested process changes were likely to improve the performance of VRSP and by how much. The simulation enabled us to undertake several experiments using different process setups. Specifically, we tested a variety of options requiring VRSP to:

- Manage ‘long’ jobs - We assumed that VRSP could predict ‘long’ jobs and subcontract these immediately, freeing up their resources for the short jobs. Subcontracting would, therefore, reduce the jobs in the ‘long tail’ of the distribution, and the new distribution reflects a more symmetric distribution. The VRSP has one important KPI, a 90% success in processing a job in a certain period. If the VRSP can predict a long job, they assume that one job would be failed. Instead of wasting resource in a failed job, the VRSP can subcontract this long job. Then, they can free up their resources to ensure the success of other jobs.
- Reduce the ‘cradle truck’ (i.e., specialist vehicle) allocation time - When reviewing the historical data, we found that there were a relatively small number of times when the specialist vehicle VRSP requirement was realized in the additional calls (i.e., the call after the original calls were greater than 5 minutes). If the most specialized vehicle is only allocated when needed, and this can be quickly determined, the allocation time and the arrival time for these jobs can be reduced. The assumption we make in this experiment is when the requirement for a specialized vehicle is defined in the original call from a consumer, the allocation time and the arrival time is reduced.
- Information completeness and accuracy to improve allocation times - We assume that when more complete and accurate information is provided, VRSP can ‘compress’ the allocation time, meaning that more of the allocated block of time per job is dedicated to the ‘value-add’ activity of reaching/driving to the consumer.
- Reduce the ‘tail’ of jobs requiring long allocation time at VRSP - Currently, there are many jobs that take a long time to be allocated; e.g., the allocation time record exceeds three hours. Such situations might occur because of unclear information at VRSP dispatch. We assume that these types of jobs can be managed. In this experiment, we generated cases where there are no jobs that take significant periods for allocation.
- Reduce the mean allocation time - Currently, based on the records, most jobs required no updated information. However, from the observation at VRSP dispatch, we observed numerous times when the VRSP dispatcher had to call ClientFirm or the consumer. Therefore, we assume that the information is not always updated on the system each time. We assume that if this information is more accurate and complete, we can reduce the average allocation time at VRSP.
- Combined changes - In this final experiment, we test the impact of all changes previously tested separately.

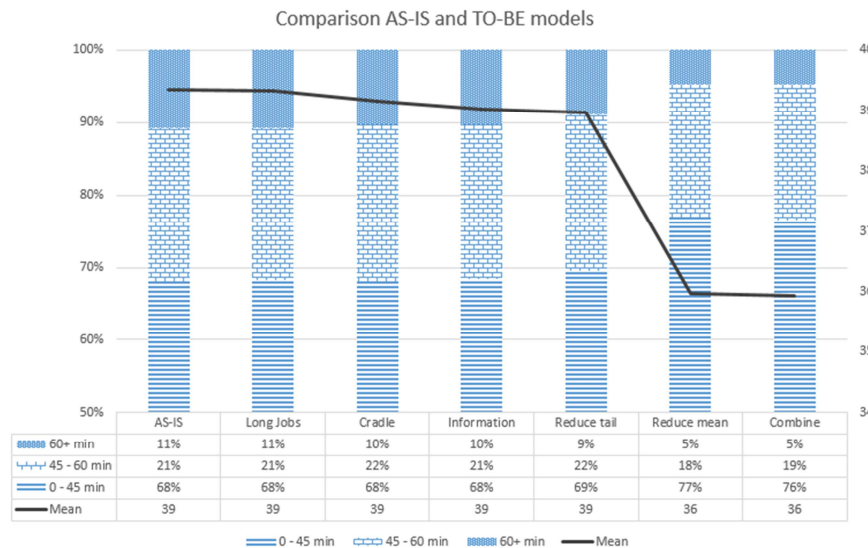


Figure 5 Comparison of the different experimental changes and simulation results focusing on the time taken to reach the consumer under a range of different experimental settings. The percentage of jobs taking over 60 minutes is shown in the top row; if the average allocation times can be reduced the percentage of jobs over 60 minutes halves.

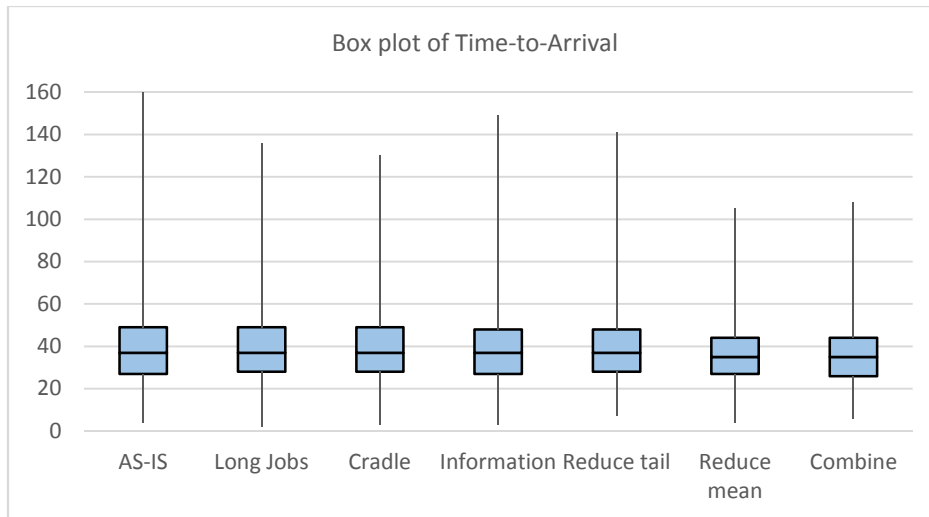


Figure 6 Box plot showing min, max, and median of Time-to-Arrival in AS-IS and TO-BE models

Table 1. Mode and Median values of Time-to-Arrival in AS-IS and TO-BE models

	Mode	Median
AS-IS	37	37
Long Jobs	37	37
Cradle	33	37
Information	34	37
Reduce tail	30	37
Reduce mean	36	35
Combine	37	35

The simulation results showed that if the information accuracy can be improved, VRSP gained 1% on the number of jobs below 60 minutes. If the allocation ability was improved (by both improving information and reducing workload at VRSP dispatch), the proportion of jobs over 60 minutes dropped from 11% to 5%.

Based on these simulation results, it become clear that reducing the time taken for the ‘allocation activity’ at VRSP could generate benefits by reducing the proportion of jobs where the time-to-arrival is more than 60 minutes. The reduction would enable VRSP to meet their subcontractor KPI. Two key efforts were required to achieve this outcome based on the receipt of information and the use of information:

1. Improving the completeness and accuracy of information passed to VRSP
2. The VRSP implementing operational changes to improve allocation activities.

There seemed to be little impact from eliminating the long jobs. We suspect that this may be because there are a relatively small number of such jobs that can be predicted with accuracy. Therefore, even elimination of all these jobs will represent only a small percentage drop in jobs over the time-threshold.

5. DISCUSSION

The preliminary analysis of the detailed process data coupled identified the ‘allocation’ activity as crucial to meeting the KPI. Based on several experimental runs in the DES modeling, we were able to determine that where the allocation activity was improved, significant changes in the overall outcomes could be impacted. The improvements rely on the transfer of complete and accurate information over the supply chain and the effective use of this information by VRSP.

5.1 The Service Supply Chain and Information Sharing

The impact of information flow was noted to have a significant impact on the overall process outcomes. While the impact was felt differently over the activities in the process, the overall impact was most acutely noted at the VRSP dispatch center; here, the team acted as the interface between the two organizations and many cases issues are problems around information needed to be resolved here.

The study results in Figure 5 indicated that a small improvement in the overall performance of this interface activity would have significant knock-on benefits to the downstream activities. Much of the required information was already being collected and transferred electronically.

ClientFirm has increasingly worked to secure more information about the consumer and encode this in the database so that it could be transferred to VRSP using EDI. The data that are required are a precise/accurate location for the pickup of the consumer, the drop-off for the consumer, and the type of fault (as this determines the most appropriate vehicle to allocate for the job.) On receipt of a job, VRSP dispatch staff making judgments about the allocation of vehicle to the job based on their experience and training. Therefore, there is further opportunity to make use of the new information and data available to them to support the decision-making process.

The modeling work and process mapping suggested two key improvements in the information flow between firms. In this way, the information flow between parties can be significantly improved and also better leveraged to present operational improvements. First, VRSP has commenced an investigation into providing a decision support system (DSS), using data received in the form of coordinate information to understand the location of open jobs and location of trucks. This better enables allocation activities to take place at the VRSP dispatch center, which had a big impact on their work.

Second, the drivers themselves frequently use their knowledge of the streets to determine the best route to a location – although the driver often must pull over to the side of the road to consult with a map book to understand the last details in the route to the exact consumer location. The use of GPS navigation device can enable them to undertake the broad route to approximately the consumer location before switching to the use of the (constantly updated) GPS navigation device for the most precise travel to the reported consumer location.

5.2 Process Integration and the Allocation Activity

Existing modeling has focused on uncertainties in demand (e.g., Coslovich et al., 2006); in our work, we find that the uncertainty relating to the flow of information is also crucial. In the service supply chain, this can be mitigated, to some degree, with improved process integration between the firms. If both firms can more effectively capture, share, and use accurate information – this should improve the decision-making within each process. Furthermore, the automation of several activities can reduce the variability and improve the performance during periods of high stress or high demand. We modeled this in the simulation experiments by using less skewed distributions for the process times for these activities.

The practical implications indicate that the skew and variability in some process activities can significantly impact the overall process; therefore, careful management of one or two activities over the entire integrated process can deliver significant benefits. Furthermore, these particular activities may not be those who appear immediately important. In our case, the activities may be seen as a secondary/supporting process and the management of information within a logistics business. However, a failure of this particular activity has significant ramifications for the ongoing, timely delivery of the service to the consumer.

Better information and the use of decision support systems can enhance the opportunity for dispatch officers to undertake more consistently their activity providing large benefits to the downstream activities. The information-uncertainty and -incompleteness represent other cause of uncertainty that must be accommodated when extending existing models. Therefore, it is another uncertainty that would need to be included in TOD models (Coslovich et al., 2006; Sungur et al., 2010).

This information must be carefully collected and shared. The process of collecting the right data, at the ClientFirm call center, relies on support from VRSP as they have the expert knowledge of the types of information that would be most useful to them. Therefore, a collaboration between the firms enables more effective acquisition of the data for use in delivering the service.

5.3 Subcontractor KPI and Seasonal Demand

For VRSP as a subcontractor, the existing KPI used to measure their performance – focused on efficiency – cannot be changed. While this subcontractor KPI established by using an ‘averaged’ workload, it fails to account for the

significant impact on the persistence of the backlogs that persist for a longer period than the peak in seasonal demand during rush hour traffic. The more seasonal the demand pattern on a daily basis, the severe the impact of the persistent backlog (Figure 5). While the use of an efficiency-focused KPI may cause difficulties for the subcontractor, there may, in fact, be very good reasons for such an efficiency-focused KPI. In this particular case, an efficiency based subcontractor KPI is valuable when the service is marketed; it is easy to understand and is, therefore, comprehensible to many consumers.

Given the existing subcontractor KPI, it is challenging for the VRSP to add additional capacity to meet the seasonal demand as this capacity would be idle for extended periods. It is also not possible for VRSP to subcontract further as all other firms face similar capacity constraints during this seasonal peak. The fluctuating and seasonal nature of demand makes it difficult to ensure that sufficient capacity is available without incurring a significant cost – is the use of backlogs counteracts the KPI and may even have an ongoing impact that deteriorates performance for a more considerable period.

5.4 Information Collection and Sharing

In contrast, the ClientFirm call center KPIs in the service supply chain have already implemented KPIs designed to ensure the ‘quality of information’ or ‘quality of outcome.’ This focus supports the flow of information by addressing the interface between the consumer-facing organization and the scheduling of the vehicles at VRSP. Therefore, call center KPIs should both support cross-organizational process efficiency while making an effort to improve system-wide outcomes. The ClientFirm call center KPIs reflect a mix of two KPIs categories. First, application of ATT to ensure that there is consideration of efficiency. Second, application of PPR, by evaluating the number of times of information is updated following the initial call. (We note that this may exclude updates to payment information or other changes required if the consumer’s circumstances become unsafe; e.g., if circumstances change during a night-time request.) Observational data indicate that the call center workers often spend considerable time speaking with consumers to elicit appropriate and full information.

Staffing levels and effort quality are two important components in the call center operations (Ren and Zhou, 2008). Effort quality indicates the effort level of agents to attend to the calls served and is directly related to overall service quality; PPR encourages effort quality (Ren and Zhou, 2008). The inclusion of PPR explicitly acknowledges effort quality in the performance measures and will encourage agents to extract accurate and complete information the first time they speak with a consumer (Ren and Zhou, 2008). The key principle of PPR is that satisfaction is only generated from served customers who experience a successful resolution.

The elicitation of appropriate information can be improved through the use of a specialist list of questions for consumers. There must be few questions to ask, they must be easily understood and answered by consumers (often in periods of stress), and they must provide useful information for VRSP. Working with trainers for the drivers, VRSP was able to determine a limited set of key questions that would be easily answered and provide sufficient supporting information to determine the cause of the problem and therefore which vehicle would be most appropriate to help the consumer. These questions can be included at the call center in ClientFirm to improve the capture of key information that will improve the effectiveness of the allocation activity in VRSP.

6. CONCLUSIONS

In this research, we aimed to identify and understand key variables that would impact on the service performance for the TOD service supply chain. We find that the uncertainty of information completeness and the need to re-evaluate the allocation of specific capacity for a given consumer is a key source of uncertainty. Using a real-world case study in empirical data, we modeled improved business processes designed to facilitate a more flow of more complete and accurate information between service firms coupled with the most effective use of the information operationally. The simulation results indicated that a small change in the management and use of information can deliver significant benefits in the overall performance of the service provision. Our research is dissimilar to most TOD research that may emphasize clustering of jobs, routing, or scheduling; we find that locational issues and information sharing and use within the service supply chain are most important. Having and using accurate information about the consumer requirements is crucial as not all vehicles are the same; the allocation (or pairing) of a vehicle to the job is a key activity that is supported by the inter-firm information sharing.

This study has other implications for other firms. Similar results are likely also to be important for other TOD organizations, particularly ambulances (i.e., as they cannot turn away work), and taxis. We also demonstrate the difficulties in adapting TOD vehicle recovery service to meet a purely efficiency based KPI that doesn’t account for seasonal variations in demand. Our results indicate that the process integration and the flow of information across the service supply chain can provide significant operational benefits. In our case, focused on inefficiency KPI, we

highlight our relatively small process changes can produce significant outcomes. These process changes need not be administratively or technologically complex; however, the process changes do require a commitment and a willingness to engage from both of the organizations involved.

One of the key limitations of this research is that we focused on a heterogeneous vehicle fleet, despite the heterogeneity displayed in the real-world problem and the additional management difficulties that this created. Therefore, future research should be focused on the dynamics of ‘capacity consumption’ over a heterogeneous fleet and the interplay of seasonal demand. The role interaction between seasonal demand and KPIs requires further examination to determine the impact of seasonality and the severity of seasonality on performance measured against the KPIs. The processes can also be addressed to examine the presence of the feedback loops and understand how these dynamics could be addressed with a more creative or dynamic KPI. Further modeling work could incorporate the update of information from the client firm to the vehicle recovery service provider, and develop an algorithm to support routing of vehicles under this additional source of uncertainty. Future research may include a more comprehensive model that accounts for the additional challenges posed by the issue of data exchange errors. These appeared to have some impact on the operational performance between the two parties.

REFERENCES

1. Anderson, E.G., Morrice, D.J., Lundeen, G., 2005. The “physics” of capacity and backlog management in service and custom manufacturing supply chains. *System Dynamics Review*, 21, 217–247. doi:10.1002/sdr.319
2. Breidbach, C.F., Reefke, H., Wood, L.C., 2015. Investigating the formation of service supply chains. *Service Industries Journal*, 35, 5–23. doi:10.1080/02642069.2014.979404
3. Caprara, A., Galli, L., Stiller, S., Toth, P., 2014. Delay-robust event scheduling. *Operations Research*, 62, 274–283. doi:10.1287/opre.2014.1259
4. Chen, D., Guy D., Fancois, V., 2008. Architectures for enterprise integration and interoperability: Past, present and future. *Computers in Industry*, 59(7), 647–659. doi: 10.1016/j.compind.2007.12.016
5. Cho, D.W., Lee, Y.H., Ahn, S.H., Hwang, M.K., 2012. A framework for measuring the performance of service supply chain management. *Computers & Industrial Engineering*, 62, 801–818. doi:10.1016/j.cie.2011.11.014
6. Cordeau, J.-F., Laporte, G., Potvin, J.-Y., Savelsbergh, M.W.P., 2007. Chapter 7 Transportation on Demand, in: Laporte, C.B. and G. (Ed.), *Handbooks in Operations Research and Management Science, Transportation*. Elsevier, pp. 429–466.
7. Corman, F., D’Ariano, A., Hansen, I.A., 2014. Evaluating disturbance robustness of railway schedules. *Journal of Intelligent Transportation Systems*, 18, 106–120. doi:10.1080/15472450.2013.801714
8. Coslovich, L., Pesenti, R., Ukovich, W., 2006. A two-phase insertion technique of unexpected customers for a dynamic dial-a-ride problem. *European Journal of Operational Research*, 175, 1605–1615. doi:10.1016/j.ejor.2005.02.038
9. Demirkan, H., & Cheng, H. K. (2008). The risk and information sharing of application services supply chain. *European Journal of Operational Research*, 187(3), 765–784. <https://doi.org/10.1016/j.ejor.2006.03.060>
10. Eisenhardt, K.M., 1989. Building theories from case study research. *Academy of Management Review*, 14, 532–550. doi:10.5465/amr.1989.4308385
11. Feinberg, R.A., Kim, I., Hokama, L., Ruyter, K. de, Keen, C., 2000. Operational determinants of caller satisfaction in the call center. *International Journal of Service Industry Management*, 11, 131–141. doi:10.1108/09564230010323633
12. Gendreau, M., Laporte, G., Semet, F., 2001. A dynamic model and parallel tabu search heuristic for real-time ambulance relocation. *Parallel Computing*, 27, 1641–1653. doi:10.1016/s0167-8191(01)00103-x
13. Gustin, C.M., Daugherty, P.J., Stank, T.P., 1995. The effects of information availability on logistics integration. *Journal of Business Logistics*, 16, 1–21.
14. Hasija, S., Pinker, E.J., Shumsky, R.A., 2008. Call center outsourcing contracts under information asymmetry. *Management Science*, 54, 793–807.
15. Horn, M.E.T., 2002. Fleet scheduling and dispatching for demand-responsive passenger services. *Transportation Research Part C: Emerging Technologies*, 10, 35–63. doi:10.1016/s0968-090x(01)00003-1
16. Jaiswal, A.K., 2008. Customer satisfaction and service quality measurement in Indian call centres. *Managing Service Quality: An International Journal*, 18, 405–416. doi:10.1108/09604520810885635
17. Lin, D., Wood, L.C., Lu, Q., 2012. Improving business incubator service performance in China: The role of networking resources and capabilities. *Service Industries Journal*, 32, 2091–2114. doi:10.1080/02642069.2011.582498
18. Mitra, S. 2013. Comparing static and dynamic policies for vehicle routing problems with backhauling and dynamic customer demands. *International Journal of Applied Logistics*, 4(2), 1–17. <https://doi.org/10.4018/jal.2013040101>

19. Powell, S.G., Schwaninger, M., Trimble, C., 2001. Measurement and control of business processes. *System Dynamics Review*, 17, 63–91. doi:10.1002/sdr.206
20. Rafaeli, A., Ziklik, L., Doucet, L., 2008. The impact of call center employees' customer orientation behaviors on service quality. *Journal of Service Research*, 10, 239–255. doi:10.1177/1094670507306685
21. Ren, Z.J., Zhou, Y.-P., 2008. Call center outsourcing: Coordinating staffing level and service quality. *Management Science*, 54, 369–383.
22. Sampson, S.E., 2000. Customer-supplier duality and bidirectional supply chains in service organizations. *International Journal of Service Industry Management*, 11, 348–364. doi:10.1108/09564230010355377
23. Sankaran, J.K., Wood, L., 2007. The relative impact of consignee behaviour and road traffic congestion on distribution costs. *Transportation Research Part B: Methodological*, 41, 1033–1049.
24. Sungur, I., Ren, Y., Ordóñez, F., Dessouky, M., Zhong, H., 2010. A model and algorithm for the courier delivery problem with uncertainty. *Transportation Science*, 44, 193–205. doi:10.1287/trsc.1090.0303
25. Umble, M., Umble, E.J., 2006. Utilizing buffer management to improve performance in a healthcare environment. *European Journal of Operational Research*, 174, 1060–1075. doi:10.1016/j.ejor.2005.02.059
26. Wang, Y., Wallace, S.W., Shen, B., Choi, T.-M., 2015. Service supply chain management: A review of operational models. *European Journal of Operational Research*, 247, 685–698. doi:10.1016/j.ejor.2015.05.053
27. Yin, R.K., 2014. *Case study research: Design and methods*, 5th ed. SAGE, Los Angeles.
28. Zhong, H., Hall, R.W., Dessouky, M., 2007. Territory Planning and Vehicle Dispatching with Driver Learning. *Transportation Science*, 41, 74–89.

Appendix 1 Statistical characteristics of gather data

According to the availability of the data, we can estimate the time needed for main these activities: the occurrence of a job, the time for allocation, arrival, loading, and delivery. Other supporting activities are considered a part of these main activities. Therefore, in the simulation model, we assume that other supporting activities such as calling the call centre take zero time.

The time needed for main activities are estimated from 8,000 jobs. by using StatFit tool in the ExtendSim software (Table 1). Moreover, as advised by VRSP, the time for each activity may depend on when during the day the task is undertaken. Therefore, we estimate the input parameters for each block of time over 24-hours, using times suggested by VRSP staff.

Table 1 Data distributions

Period	Job Occurrence (Exponential Distribution)	Time for Allocation (Weibull Distribution ²)			Time for Arrival (Weibull Distribution)			Time for Loading (Weibull Distribution)			Time for delivery (Weibull distribution)		
	Interval minute	Location	Shape	Scale	Location	Shape	Scale	Location	Shape	Scale	Location	Shape	Scale
00:00 - 06:59	1.17	0	1.56	6.26	0	2.04	24.7	0	1.78	12.4	0	1.58	20.2
07:00 - 08:59	0.22	0	2.05	8.03	0	2.08	35.8	0	2.49	16.7	0	2.96	25.6
09:00 - 11:59	0.18	0	2.05	8.78	0	2.5	29.2	0	2.36	15.8	0	2.77	24.2
12:00 - 15:59	0.22	0	2.25	9.06	0	2.48	28.3	0	2.26	15.2	0	2.79	25
16:00 - 18:59	0.31	0	2.06	8.41	0	2.55	29.7	0	2.1	13.7	0	2.45	27
19:00 - 23:59	0.70	0	1.94	7.4	0	2.34	27.8	0	2.06	13	0	2.7	23.8

² The Weibull distribution is a commonly used continuous probability distribution. It is often used to represent situations where there is a ‘stretched’ tail or a ‘skewness’ to the data; in this case, it was used as while most jobs occur close to the ‘average’ values, there are a small number of jobs that take significantly longer, creating the stretched tail.

Appendix 2 Experimental settings**Appendix 2.1 Management of ‘long’ jobs**

In the TO-BE model, the long jobs are predicted and forwarded to contractors immediately. Therefore, the VRSP truck drivers do not need to handle these long jobs. This helps to reduce the arrival time to the vehicle location. The Arrive at Vehicle Location is estimated by eliminating the long jobs (time to arrive more than 90 minutes) out of 8000 recent jobs. All these parameters are statistical significant.

Table 2 The Time to Arrival (Weibull distribution)

Period	Location	Shape	Scale
00:00 - 06:59	0	2.03	24.6
07:00 - 08:59	0	2.1	35.6
09:00 - 11:59	0	2.5	29.2
12:00 - 15:59	0	2.47	28.2
16:00 - 18:59	0	2.53	29.6
19:00 - 23:59	0	2.33	27.7

Appendix 2.2 Reduction in ‘cradle truck’ allocation time

Except the activities Allocation jobs to truck driver and Arrival to jobs, other activities in the TO-BE model are similar to those in the AS-IS model.

Table 3 The Time for Allocation (Weibull distribution)

Period	Location	Shape	Scale
00:00 - 06:59	0	1.56	6.25
07:00 - 08:59	0	2.05	8.03
09:00 - 11:59	0	2.05	8.78
12:00 - 15:59	0	2.25	9.06
16:00 - 18:59	0	2.06	8.41
19:00 - 23:59	0	1.94	7.4

Table 4 The Time for Arrival (Weibull distribution)

Period	Location	Shape	Scale
00:00 - 06:59	0	2.03	24.7
07:00 - 08:59	0	2.08	35.8
09:00 - 11:59	0	2.5	29.2
12:00 - 15:59	0	2.47	28.2
16:00 - 18:59	0	2.54	29.7
19:00 - 23:59	0	2.35	27.7

Appendix 2.3 Reduction in the allocation time at VRSP

Better quality information leads to the ‘right first time’ and faster time to get the job correct and to the driver. We estimated the allocation time in the TO-BE model by eliminating 221 jobs having additional calls after the original calls more than 5 minutes. The new parameter for activities Allocation jobs to truck drivers and Arrival to jobs are as follows.

Table 5 The Time for Allocation (Weibull distribution)

Period	Location	Shape	Scale
00:00 - 06:59	0	1.55	6.25
07:00 - 08:59	0	2.05	8.04
09:00 - 11:59	0	2.05	8.75
12:00 - 15:59	0	2.26	9.09
16:00 - 18:59	0	2.06	8.38
19:00 - 23:59	0	1.93	7.39

Table 6 The Time for Arrival (Weibull distribution)

Period	Location	Shape	Scale
00:00 - 06:59	0	2.03	24.7
07:00 - 08:59	0	2.08	35.8
09:00 - 11:59	0	2.49	29.1
12:00 - 15:59	0	2.47	28.3
16:00 - 18:59	0	2.54	29.7
19:00 - 23:59	0	2.36	27.7

Appendix 2.4 Reduction of jobs having too long allocation time at VRSP

This change eliminates the jobs having too long allocation time. The average time for allocation is kept as in the current process. The allocation time is still following the Weibull distribution. We reduced the long-tail of the allocation time. The new parameters of the allocation time are: Location = 2; Shape = 3.2; and, Scale = 6.2

Appendix 2.5 Reduce the allocation time

This change assumes that the allocation time at VRSP is reduced. We can reduce the average time and the long-tail of the allocation time. The new parameters of the allocation time are Location = 2; Shape = 3.2; and, Scale = 5.5.

Appendix 2.6 Combined changes

In this experiment, the parameter for activities Allocation jobs to truck drivers and Arrival to jobs are as follows. Parameters for the Weibull distribution for Time for Allocation were changed to Location = 2; Shape = 3.2; and, Scale = 5.5.

Table 2 The Time for Arrival (Weibull distribution)

Period	Location	Shape	Scale
00:00 - 06:59	0	2.03	24.6
07:00 - 08:59	0	2.09	35.6
09:00 - 11:59	0	2.49	29.1
12:00 - 15:59	0	2.47	28.2
16:00 - 18:59	0	2.53	29.6
19:00 - 23:59	0	2.35	27.6