Universidad Autónoma de Nuevo León

Facultad de Ingeniería Mecánica y Eléctrica

Subdirección de Estudios de Posgrado

Dynamic Planning and Real-Time Monitoring of Ready-Mixed Concrete Delivery Problem

por

Jorge Garza Cavazos

como requisito parcial para obtener el grado de

doctorado en ingeniería

con Especialidad en Ingeniería de Sistemas

Febrero 2021

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Los miembros del Comité de Tesis recomendamos que la Tesis «Dynamic Planning and Real-Time Monitoring of Ready-Mixed Concrete Delivery Problem», realizada por el alumno Jorge Garza Cavazos, con número de matrícula 1770321, sea aceptada para su defensa como requisito para obtener el grado de Doctor en Ingeniería con Especialidad en Ingeniería de Sistemas.

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Resumen

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Universidad Autónoma de Nuevo León.

Facultad de Ingeniería Mecánica y Eléctrica.

Título del estudio: Planeación Dinámica y Monitoreo en Tiempo Real del Problema de Entrega de Concreto Mezclado.

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Objetivos y método de estudio: La industria del concreto se ha convertido en una de las industrias más importantes, ya que el concreto se utiliza para la construcción de edificios, casas y la construcción de infraestructura pública. Un problema particular es satisfacer la demanda de los clientes mediante la entrega de concreto desde plantas con camiones. Para cada cliente, una salida diaria de camiones es horario. Sin embargo, algunos factores pueden afectar el cronograma establecido, como que el concreto es perecedero (tiempo de entrega máximo antes de que se endurezca), que los camiones y / o plantas puedan fallar (paradas de emergencia o problemas eléctricos), o que los trabajadores no se presenten a los horarios de trabajo establecidos. Estos factores generan insatisfacción del cliente y pérdidas de la empresa. El problema es altamente combinatorio y, por lo tanto, varios trabajos lo resuelven mediante algoritmos de optimización, pero ninguno logra capturar todo el proceso.

Por lo tanto, este trabajo busca mantener los horarios establecidos a través de una herramienta multiplataforma. El núcleo de la herramienta es la dinámica de los sistemas, como lo ha demostrado, en aplicaciones industriales, tener un buen rendimiento y reproducir fácilmente las operaciones diarias. El objetivo es minimizar la distancia y el tiempo total de viaje del cliente a la planta, considerando las características especiales de los servicios del cliente (es decir, el concreto). La asignación debe reprogramarse, ya que se pueden producir cambios inesperados, como cancelaciones de servicios, llegadas tardías de clientes o se superan los tiempos de servicio al cliente.

Contribuciones y conlusiones: El uso de la herramienta está destinado a mejorar el servicio al cliente y la empresa. Las decisiones de la herramienta incluyen la igualdad de uso de la planta en la empresa (balance de servicios) teniendo en cuenta qué servicios deben ser entregados por ciertas plantas y continuar entregando una planta específica a un cliente que inicia su servicio desde esa planta. Además, mejorar la asignación de servicios al cliente y camiones. Presentamos los resultados obtenidos luego de implementar esta herramienta en una empresa concreta real. Fuimos capaces de mejorar el tiempo de servicio al cliente.

Firma de la asesora: ____

Dra. Sara Verónica Rodríguez Sánchez

Abstract

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Facultad de Ingeniería Mecánica y Eléctrica.

Title of the study: Dynamic Planning and Real-Time Monitoring of Ready-Mixed Concrete Delivery Problem.

Number of pages: 145.

Objectives and methods: The concrete industry has become one of the most important industries since the concrete is used for the construction of buildings, houses, and elaboration of public infrastructure. One particular problem is to satisfy the demand of clients through deliver the concrete from plants with trucks. For each client, a daily truck departure is schedule. Nevertheless, some factors may affect the established schedule such as the concrete is perishable (maximum delivery time before it hardens), trucks and/or plants can fail (emergency stops or electrical problems), or workers may not show up at established work schedules. These factors generate client dissatisfaction and company losses. The problem is highly combinatorial and thus several works solve it by optimization algorithms but none success to capture the whole process.

Therefore, this work seeks to maintain established schedules through a multi-platform tool. The core of the tool is systems dynamics as it has proven, in industry applications, to have good performance and easily to reproduce daily operations. The objective is to minimize the distance and the total travel time from the client to the plant considering special characteristics of the client services (i.e, concrete). The assignment needs to reschedule as unexpected changes may occur such as cancellations of services, late arrivals with customers, or client service times are exceeded.

CONTRIBUTIONS AND CONCLUSIONS: The use of the tool is intended to improve customer service and company. Decisions of the tool include the equality of plant usage in the company (balance of services) considering which services should be delivered by certain plants and continue deliver from a specific plant to a costumer that initiates its service from that plant. Also, improve allocation of customer services and trucks. We present the results obtained after implementing this tool in a real concrete company. We were capable to improve customer service time arrivals.

Signature of the advisor: ______________________________

Dra. Sara Verónica Rodríguez Sánchez

Chapter 1

Introduction

From the last years, production and delivery of *ready-mixed concrete* has become one of the most important, demanded, and automated industry. This kind of industry is characterized by the dynamic and uncertain environment caused by producing a highly perishable product with a high variability in its demand. The concrete production planner must be monitoring timeliness and flexibility on ready-mixed concrete plants and construction sites, in order to design an efficient delivery schedule considering the acquisition of raw materials, preparation of the mixture, loading and dispatching the trucks, delivering and unloading concrete into the construction site, and truck returning to the plant, among others. However, in daily basis, it is common that incidents occur such as: trucks and plants malfunction, electricity problems, and/or absenteeism of workers. These incidents imply modifications on the scheduled truck routes and ready-mixed concrete production. As the day passes, the modifications of the delivery schedule increases as early delivery are attended on next hours from its schedule hour. This is called the *domino effect* and usually requires additional resources to satisfy the scheduled customer sites according to the planned demand on the day. These modifications imply a late delivery of concrete to customers yielding a problem for both, the customer and the company. Focusing on the customer, a late delivery results in construction delays and interruption of concrete discharge which lead to structure-building problems, to mention, the *cold joint*, also known as cold seam, a weaker concrete than the surrounding concrete, that is a potential plane of fracture, it requires to replace all the concrete. On the other hand, focusing on the company, a late delivery results in concrete hardening inside the trucks. Also, in orders with several deliveries, the delays can cause a supply disorder, generating truck queues waiting for discharging the concrete in the construction site, delaying future deliveries, and affecting other customers and next schedules. These problems result in wasted time that could have been used to serve another construction generating the increase of general operation costs when the ready-mixed concrete is not delivered into the agreed schedule. Based on the presented problematic, general operation of concrete companies seek to increase the cost effectiveness of trucks, delivery, and plants, since trucks acquisition and the plants construction is approximately the same, purchasing new trucks becomes not an option. Therefore, it is important to streamline current resources, meanly plants and trucks to delivery on time, whenever is possible, to each of the construction sites.

Most concrete dispatch and planning decisions are complex with many dynamic variables therefore modifications of the initial schedule constantly happened and continuously must be planned and re-planned in short periods of time. The efficiency of the proposed solutions depends highly on the knowledge and skill of the planners and dispatchers who, with their experience and knowledge, decide among possible alternatives the efficient use of the company's critical resources such as plants, trucks, and vehicles operators. The information to be used by experts is limited since they do not have the discernability of key points such as the visibility of the demand coverage and the costs of the different supply options. Two scenarios were distinguished where the optimization engine's recommendations are not reasonable for planners and dispatchers. In the first scenario, the solution is not understood by the planner. To solve this problem, the help of the expert in the mathematical model is needed to support the understanding and conviction towards the planner that it is a viable and optimal alternative. The problem is generated because the optimization engines are considered as a black box for the planners and dispatchers and it is not natural for them to understand the result of all the mathematical calculations and all the mathematical properties that make up the solution. In the second scenario, it is detected that the solution delivered by the engine is contradictory to the reasoning of the planner. To deal with this problem, the planner must convince the expert that the solution provided by the engine is not feasible for day-to-day operation. The main reasons for this scenario are: 1) there are business rules and operational restrictions that have difficulty incorporating a mathematical model; and 2) despite using high-capacity computing servers, some restrictions are relaxed that are possible to model mathematically, but which considerably increase the size of the model and with this the solution time.

This work is based on the case study of an international concrete company of Mexico which has a complex scheduling problem. The principal issue of the concrete company is the delivery of concrete on a construction site in a specific time window and maximizing the use of the available fleet. Some of the difficulties to attend this issue is that are the trucks are located in farest plants, the workers not arriving on time (for example, by sleepless of the worker or traffic), a delay in the assign service to an available truck in plant, large stay time of trucks in plants and/or with clients, in big buildings, the delay of the starting time due to the different preparations that require, and clients that have large demand of concrete change unexpected. The characteristics of the problem include order taking, planning, dispatching, and delivering the concrete. The entire process had to be analyzed and considered to preclude any possible backlogs.

Currently, in the company under study, it is desirable that each truck makes at least four trips daily, but in practice less than three trips are made. This problem is caused by accepting few orders and considering only the maximum capacity of each plant (a no risk point of view), but because the dynamism of day-on-day operations and the variability in demand, modifications in the planning are presented that generate, in most cases, idle capacity in the company.

In addition, in every truck is installed a Gps that allows on-line tracking of the location of the truck. In a specific day, the company delivers around 700 - 1 000 loads using about 20 concrete plants and 200 trucks to complete the task . Modest five minutes on every load would be saving huge amounts to the company up to $1 000 000 annual. As the efficiency of the dispatching process depends on the dispatcher skills. If a effective dispatcher is not present, the impact of the company efficiency is affected negatively. On the other hand, process that cost and time-consuming such as plant scheduling, or arrival times for drivers are need to be addressed in order to maintain efficiency of the company. Therefore, the company needs a decision-support tool which generate savings in production, schedule, and dispatch processes. These savings help to reduce stress of dispatchers, schedulers, and plant managers. Also, the training times is reduced as new dispatchers manage to understand in a short period of time the whole concrete dispatch problem.

To address the concrete company problem, in this work we employ a dynamic engine to re-assigning orders from customers, and efficiently adjust the ready-mixed concrete production and truck dispatching schedules whenever an ready-mixed concrete incident occur during the operational day. This resource allocation problem can be modeled mathematically, however acquiring the optimum solution in such a complex and large-scale problem is computationally intractable, moreover, the problem is characterized as a classic non-deterministic polynomial-time hard ($\mathcal{NP}$-*hard*) problem. The proposed solution is validated with actual operating data from the ready-mixed concrete company under study.

This work begins by reviewing the existing proposed solutions, which use optimization engines based on mathematical models, perform acceptably when the demand for concrete is equal to or less than 85% of the installed capacity, but their efficiency is markedly decreased when the demand exceeds 85%. In this case, model recommendations are often unreasonable for operation and therefore are not accepted by planners. The objective of the research is to understand the causes of the limitations of the mathematical models and propose alternative solutions that consider the greatest number of elements in the production and dispatch of concrete. To address the company specs, this work employs an engine to re-assigning the orders, that adjusts e effectively the ready-mixed concrete production and truck dispatching schedules following ready-mixed concrete incidents. The use and enablement of a support engine for strategic and operational decision-making which suggests better alternatives in the allocation of critical resources is necessary to aim lower operational costs and improve client service experience. Theoretically, this resource allocation problem can be modeled mathematically, however acquiring the optimum solution in such a complex and large-scale problem is computationally intractable, moreover, the problem is characterized as a classic non-deterministic polynomial-time hard (NP-hard) problem. The proposed solution is validated with actual operating data from the ready-mixed concrete company under study. Also, the proposed solution assist company dispatchers and operators by giving (1) the feasibility of accepting additional orders, (2) the arrival times for drivers reporting to work, (3) the scheduling of all orders, (4) the real-time assignment of drivers to delivery loads, (5) the dispatching of these drivers to customers and back to plants, and (6) the scheduling of truck loading at the plants. These determinations are made by mathematical models incorporating exact optimization techniques.

1.1 Hypothesis

It is possible to increase the cost effectiveness of ready-mixed concrete operation using a dynamic planning engine that assigns the orders to its closer plants from customer construction sites and a visualization tool to monitor the process of ready-mixed concrete to opportunely respond in daily operations.

1.2 Objective

Find an efficient way of allocate resources at the lowest cost and distance using a re-assignment tool with real-time monitoring.

1.3 Structure of the Thesis

The remainder of the thesis is organized as follows: Chapter 2 presents the background of theoretical concepts used in the elaboration of this thesis: vehicle routing problem, traveling salesman problem, and ready-mixed concrete, among others. Also, in Chapter 2 it is described a literature review relative to our problem, including different alternatives that use mathematical or theoretical approaches to solve the ready-mixed concrete delivery problem. Chapter 4 describes dynamic and visualization tools used to improve the actual solution in the company of the ready-mixed concrete delivery problem, and the algorithm to assign the orders to ready-mixed concrete plants. Chapter 6 discusses the implementation of the model and the numerical experiments performed. Finally, Chapter 7 concludes the present work and discusses directions for future work.

Chapter 2

Background

In this chapter, we present the theory to better understand the proposed work that addresses the ready-mixed concrete delivery problem. This problem is one of the most famous problems in literature, the vehicle routing, in this approach is only used to assign trucks to plants or viceversa. Although this problem has been studied and trying to solve by academics, none find a good solution in a reasonable period of time for problems with complexity and dynamics, as the ready mixed concrete delivery problem. Because of that, this work will present a system dynamic model based on mathematical models, differential equations, and simulation. Specifically, in this work, we focus on agent based simulation using a software called iThink from Stella Architech and Isee Systems. This software use block and structure models to represent the interactions between the objects (plants, trucks, and customers) involved in the ready-mixed concrete delivery problem. Therefore, the theory presented include the definition of mathematical models, simulation, differential equations, vehicle routing problem, centroid, system dynamics, and history of Isee Systems. The general considerations of the ready-mixed concrete delivery problem are presented in Chapter 3 and the theory of dynamic programming and modeling is presented in Chapter 4.

2.1 Mathematical Models

The relationship between variables, parameters, entities are describes using mathematics. This description is called a *mathematical model* that permits to study behaviors of complex real world systems. There are different classifications of the models according to their input information, representation, randomness, or application [38]:

- The input information can be based on: explanations about causes and natural mechanisms (heuristic model), or direct observations of an experiment of the studied phenomena (empiric model).
- The figures, graphics, or descriptions are used to represent the mathematical model to predict in which direction the system is going. The description in which a value is decreasing or increasing without any information is called a qualitative model, or if the change of a value is described with formulas and mathematical algorithms the description is called quantitative model.
- The randomness in the model can happen if the result is always the same as the data used has no variations (deterministic), or if the result is unknown and only the probability of some aspects of the process are known (stochastic).
- Three types of application are simulation that describes measured situations in a precise or a random way in order to predict what happens in a concrete situation, optimization to solve a problem by obtaining the exact value that meets the requirements and structure of the problem, and control to help to determine new measures, variables or parameters in order to improve the results of the system.

The *simulation of a process* consists in the representation of a process or phenomena with a logic-mathematical model capturing its particular behavior [57]. It is a useful tool in the engineering, because of the detailed description that is capable to show for a process. Some types of simulations can be modeled using discrete events, agents theory, or differential equations [44, 61, 79]. The follow section continues with the history, description, and some basic concepts to understand how a simulation is performed.

2.2 Simulation

Simulation is used in many contexts, such as simulation of technology for performance optimization, safety engineering, testing, training, education, and video games. Often, computer experiments are used to study simulation models. Simulation is also used with scientific modelling of natural systems or human systems to gain insight into their functioning, [2] as in economics. Simulation can be used to show the eventual real effects of alternative conditions and courses of action. Simulation is also used when the real system cannot be engaged, because it may not be accessible, or it may be dangerous or unacceptable to engage, or it is being designed but not yet built, or it may simply not exist [3].

Key issues in simulation include the acquisition of valid source information about the relevant selection of key characteristics and behaviours, the use of simplifying approximations and assumptions within the simulation, and fidelity and validity of the simulation outcomes. There are so many different types of simulation, therefore, we only present those that are for interest to the present work:

- *Interactive simulation* is a special kind of physical simulation, often referred to as a human in the loop simulation, in which physical simulations include human operators, such as in a flight simulator, sailing simulator, or a driving simulator.

- *Continuous simulation* is a simulation where time evolves continuously based on numerical integration of Differential Equations [5].
- *Discrete event simulation* is a simulation where time evolves along events that represent critical moments, while the values of the variables are not relevant between two of them or result trivial to be computed in case of necessity [6]
- *Stochastic simulation* is a simulation where some variable or process is regulated by stochastic factors and estimated based on Monte Carlo techniques using pseudo-random numbers, so replicated runs from same boundary conditions are expected to produce different results within a specific confidence band [5]
- *Deterministic simulation* is a simulation where the variable is regulated by deterministic algorithms, so replicated runs from same boundary conditions produce always identical results.
- *Hybrid simulation* (sometime *combined simulation*) corresponds to a mix between continuous and discrete event simulation and results in integrating numerically the differential equations between two sequential events to reduce the number of discontinuities [7].

To describe the accuracy of a simulation and how closely it imitates the real-life counterpart it is used the simulation fidelity. This can be broadly classified in three categories: *low*, *medium*, and *high*. Specific descriptions of fidelity levels are subject to interpretation but the following generalization can be made:

- **Low**: the minimum simulation required for a system to respond to accept inputs and provide outputs.
- **Medium**: responds automatically to stimuli, with limited accuracy.
- **High**: nearly indistinguishable or as close as possible to the real system.

A *computer simulation* (or *sim*) is an attempt to model a real-life or hypothetical situation on a computer so that it can be studied to see how the system works. By changing variables in the simulation, predictions may be made about the behaviour of the system. It is a tool to virtually investigate the behaviour of the system under study [1]. Another important part that is gain insight into the operation and modeling of many natural systems in physics, chemistry, biology, human systems, economics, social science, and engineering systems is the *computer simulation*. A good example of the usefulness of using computers to simulate can be found in the field of network traffic simulation. In such simulations, the model behaviour will change each simulation according to the set of initial parameters assumed for the environment. Also, in the problems that we try to solve in this work the ready-mixed concrete delivery problem have this kind of issues.

Traditionally, the formal modeling of systems has been via a mathematical model, which attempts to find analytical solutions enabling the prediction of the behaviour of the system from a set of parameters and initial conditions. Computer simulation is often used as an adjunct to, or substitution for, modeling systems for which simple closed form analytic solutions are not possible. There are many different types of computer simulation, the common feature they all share is the attempt to generate a sample of representative scenarios for a model in which a complete enumeration of all possible states would be prohibitive or impossible.

Several software packages exist for running computer-based simulation modeling (e.g. Monte Carlo simulation, stochastic modeling, multimethod modeling) that makes all the modeling almost effortless. We use a new software called iThink from Stella Architect as it has become one of the most used software for business modeling due to the ability to capture real-time process. The history and some characteristics of this software is presented in the following section.

2.3 Vehicle Route Problem

The *vehicle routing problems* (VRP) have very important applications in the area of distribution management such as ready-mixed concrete delivery problem. This is an extension of the *traveling salesman problem* (TSP) which describes a salesman who must travel between n cities without care of the order as long as he visits each one during his trip, and finishes where he was at first. Each city is connected to others, each of the links between the cities has one or more weights (or the cost) attached. The salesman wants to keep both the costs, as well as the distance he travels as low as possible.

In the VRP, a number of capacity-limited vehicles must be scheduled, around a number of customers. Hence, in addition to the sequencing of the customers to be visited (the traveling salesman problem) one has to decide which vehicles visit which customers. Each customer has a known demand (assumed to be of one commodity, although it is possible, easily to extend to more than one commodity). Hence the limited vehicle capacities have to be taken into account. In addition, there are often time window conditions requiring that certain customers can only receive deliveries between certain times.

The VRP can formally be defined as follows. Let $G = (N, A)$ be a graph where V is the vertex set and A is the arc set. One of the vertices represents the depot at which a fleet of m identical vehicles of capacity Q is based, and the other vertices represent customers that need to be serviced. With each customer vertex v_i are associated a demand q_i and a service time s_i. With each arc (v_i, v_j) of A are associated a cost c_{ij} and a travel time t_{ij} [47]. The VRP consists in finding a set of routes such that:

- Each route begins and ends at the depot;
- Each customer is visited exactly once by exactly one route;
- The total demand of the customers assigned to each route does not exceed Q;
- The total duration of each route (including travel and service times) does not exceed a specified value L;
- The total cost of the routes is minimized.

A feasible solution for the problem thus consists in a partition of the customers into m groups, each of total demand no larger than Q, that are sequenced to yield routes (starting and ending at the depot) of duration no larger than L.

2.3.1 Time Windows

The *VRP with time windows* (VRPTW) is the extension of the capacitated VRP in which capacity constraints are imposed and each customer i is associated with a time interval $[a_i, b_i]$, called a *time window*. The service of each customer must start within the associated time window, and the vehicle must stop at the customer location for s_i time instants. Moreover, in case of early arrival at the location of customer i, the vehicle generally is allowed to wait until time instant a_i, that is, until the service may start. Normally, the cost and travel-time matrices coincide, and the time windows are defined by assuming that all vehicles leave the depot at initial time (time instant 0). Additionally, observe that the time window requirements induce an implicit orientation of each route even if the original matrices are symmetric. Therefore, VRPTW normally is modeled as an asymmetric problem. VRPTW consists of finding a collection of exactly K simple circuits with minimum cost, and such that:

- each circuit visits the depot vertex;
- each customer vertex is visited by exactly one circuit;
- the sum of the demands of the vertices visited by a circuit does not exceed the vehicle capacity, C; and
- for each customer i, the service starts within the time window, $[a_i, b_i]$, and the vehicle stops for S time instants.

VRPTW is $\mathcal{NP}$-hard in the strong sense, since it generalizes the capacitated VRP, arising when $a_i, = 0, b_i = +\infty, \forall i \in V \backslash 0$.

2.4 Center of Gravity Method

The monitoring tool of the proposed approach uses the center of gravity method to aggregate the demand of customers in a a map. Therefore it is presented the theory behind this algorithm.

The *center of gravity method*, also know as COG method, is a continuous location method based on the lowest total transportation costs [41]. It is an approach that seeks to compute geographic coordinates for a potential single new facility that will minimize costs. This method involves:

- Determining the volumes by source and destination point.
- Determining the transportation costs based on $unit/mi$.
- Overlaying a grid to determine the coordinates of and/or destination points
- Finding the weighted center of gravity for the graph.

The facility location is defined by: $\bar{X} = \frac{\sum_i V_i R_i X_i}{\sum_i V_i R_i}$; $\bar{Y} = \frac{\sum_i V_i R_i Y_i}{\sum_i V_i R_i}$

where:

V_i = volume flowing from (to) point i.

R_i = transportation rate to ship V_i from (to) point i.

X_i, Y_i = coordinate points for point i.

$\bar{X}, \bar{Y}$ coordinate points for facility to be located.

The COG method does not necessarily give optimal answers, but will give good answers if there area large numbers of points in the problem (greater than 30) and the volume for any one point is not a high proportion of the total volume. However, optimal locations can be found by the exact center of gravity method:

$$\bar{X^n} = \frac{\sum_i V_i R_i X_i / d_i}{\sum_i V_i R_i / d_i},\ \bar{Y^n} = \frac{\sum_i V_i R_i Y_i / d_i}{\sum_i V_i R_i / d_i}$$

where

$d_i = \sqrt{(X_i - \bar{X^n})^2 + (Y_i - \bar{Y^n})^2}$ and n is the iteration number.

If any company wants to reduce their cost using the COG, it must to follow this process:

- Place existing warehouse, fulfillment center, and distribution center locations in a coordinate grid.
- Place the grid on an ordinary map.
- The relative distances must be noted.
- Calculate the coordinates of the two-dimensional point that meets the distance and volume criteria.

Benefits of this method:

- Find the fastest route taking into account the traffic or environmental problems that may exist.
- Reduce the cost and generates profits.
- Help to take decision.
- Improves customer service.
- Delivery of products is just-in-time; the goal of this technique is to reduce or eliminate the need for inventory.

Disadvantage: The calculations can change from one moment to another due to the information is in real time and in the case of traffic or environment does not always behave the same.

2.5 Clustering and Data Compression

When the company knows the behavior of the customers and their demand, it can be used the concept of *clustering*. Using clustering permits to group a set of objects with similar properties in the same group (*cluster*) than other objects in other groups (*clusters*). The task performed in clustering is commonly used in exploratory data mining and statistical analysis, also used in many fields such as image analysis, computer graphics, bioinformatics, among others.

To perform cluster analysis, there are no such a general algorithm, depends on the structure of the problem analyzed. Various algorithms can achieve the solution but differ significantly in their notion of which is the cluster and how to find them. Typical uses of cluster group based on distances between cluster members, dense areas of data spaces, intervals or particular statistical distributions. These considerations make clustering a multi-objective optimization problem. To chose the appropriate clustering algorithm and set the parameters of it, individual data set and the intended use of results need to be considered. Therefore the task to select an algorithm is not automatic, an iterative process is needed to discover the correct algorithm for the problem involving in some cases trial and failure, and the modification of data and model parameters to achieve desire properties.

2.5.1 Types of Models

As the definition of cluster cannot be precise, many clustering algorithms are been develop but the general idea is that a group of data objects are needed. The properties of the data studied can lead to different cluster models and therefore the understanding of the differences between the various algorithms is the key to select the model.

Usual cluster models are based on *conectivity*, *centroid*, *distribution*, *density*, *subspace*, *group*, *graph*, *neural*. Despite of the model, cluster can be classified in *hard* (each object belongs to a cluster or not) and *soft* (each object belongs to each cluster to a certain degree, for example, a likelihood of belonging to the cluster).

Soft clustering is also called *fuzzy* clustering. Also, finer distinctions are possible in clustering: *strict partitioning* (each object belongs to exactly one cluster), *strict partitioning with outliers* (objects can also belong to no cluster, and are considered outliers), *overlapping* (objects may belong to more than one cluster; usually involving hard clusters), *hierarchical* (objects that belong to a child cluster also belong to the parent cluster), and *subspace* (while an overlapping clustering, within a uniquely defined subspace, clusters are not expected to overlap).

2.5.2 Algorithms

The categorization of clustering algorithms are based on their cluster model as seen in the previous section. As mentioned previously, there is no correct way to choose a cluster algorithm but some experimental or mathematical reasons can be used to decide which cluster model is preferred over another [46]. In the following paragraphs we only expose the most used cluster algorithms (there are possible over one hounded published clustering algorithms), not all provide the model for the clusters an thus can not easily be categorized.

- *Connectivity based clustering*, also known as *hierarchical clustering*, is based than two or more objects are related to those that are closer than the objects far away. These kind of algorithms use distance as the connection between objects and clusters. Therefore, a cluster is defined as the maximum distances needed to connect parts of the cluster. Using different distance leads form different clusters, which can be represented using a *dendogram* (a tree diagram frequently used to illustrate the arrangement of the clusters produced by hierarchical clustering). The algorithms based on connectivity do not provide a single partition of the data set, but instead provide an extensive hierarchy of clusters that merge with each other at certain distances.

- In *centroid-based clustering*, clusters are represented by a central vector, which may not necessarily be a member of the data set. When the number of clusters is fixed to k, k-means clustering gives a formal definition as an optimization problem: find the k cluster centers and assign the objects to the nearest cluster center, such that the squared distances from the cluster are minimized.

- In *density-based clustering*, clusters are defined as areas of higher density than the remainder of the data set. Objects in these sparse areas, which are required to separate clusters, are usually considered to be noise and border points.

  The most popular density based clustering method is DBSCAN. In contrast to many newer methods, it features a well-defined cluster model called "density-reachability". It is based on connecting points within certain distance thresholds. However, it only connects points that satisfy a density criterion, in the original variant defined as a minimum number of other objects within this radius. A cluster consists of all density-connected objects (which can form a cluster of an arbitrary shape, in contrast to many other methods) plus all objects that are within these objects' range. Another interesting property of DBSCAN is that its complexity is fairly low, it requires a linear number of range queries on the database, and that it will discover essentially the same results (it is deterministic for core and noise points, but not for border points) in each run, therefore there is no need to run it multiple times.

2.5.3 Evaluation and Assessment

Evaluation (also called *validation*) of clustering results is as difficult as the clustering itself [39]. Popular approaches involve "internal" evaluation, where the clustering is summarized to a single quality score, "external" evaluation, where the clustering is compared to an existing "ground truth" classification, "manual" evaluation by a human expert, and "indirect" evaluation by evaluating the utility of the clustering in its intended application [8].

Internal evaluation measures suffer from the problem that they represent functions that themselves can be seen as a clustering objective. For example, one could cluster the data set by the Silhouette coefficient; except that there is no known efficient algorithm for this. By using such an internal measure for evaluation, we rather compare the similarity of the optimization problems,[32] and not necessarily how useful the clustering is.

External evaluation has similar problems: if we have such "ground truth" labels, then we would not need to cluster; and in practical applications we usually do not have such labels. On the other hand, the labels only reflect one possible partitioning of the data set, which does not imply that there does not exist a different, and maybe even better, clustering.

Neither of these approaches can therefore ultimately judge the actual quality of a clustering, but this needs human evaluation,[32] which is highly subjective. Nevertheless, such statistics can be quite informative in identifying bad clusterings,[33] but one should not dismiss subjective human evaluation.[33]

2.5.3.0 Internal evaluation

When a clustering result is evaluated based on the data that was clustered itself, this is called internal evaluation. Those that use a gold standard are called external measures and are discussed in the next section - although when they are symmetric they may also be used as measures between two clusters for internal evaluation. These methods usually assign the best score to the algorithm that produces clusters with high similarity within a cluster and low similarity between clusters. One drawback of using internal criteria in cluster evaluation is that high scores on an internal measure do not necessarily result in effective information retrieval applications.[34] Additionally, this evaluation is biased towards algorithms that use the same cluster model. For example, k-means clustering naturally optimizes object distances, and a distance-based internal criterion will likely overrate the resulting clustering.

Therefore, the internal evaluation measures are best suited to get some insight into situations where one algorithm performs better than another, but this shall not imply that one algorithm produces more valid results than another.[4] Validity as measured by such an index depends on the claim that this kind of structure exists in the data set. An algorithm designed for some kind of models has no chance if the data set contains a radically different set of models, or if the evaluation measures a radically different criterion.[4] For example, k-means clustering can only find convex clusters, and many evaluation indexes assume convex clusters. On a data set with non-convex clusters neither the use of k-means, nor of an evaluation criterion that assumes convexity, is sound.

The following methods can be used to assess the quality of clustering algorithms based on internal criterion:

- The *Davies–Bouldin index* can be calculated by the following formula:

$$DB = \frac{1}{n}\sum_{i=1}^{n} \max_{j \neq i} \left(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)} \right) \tag{2.1}$$

  where n is the number of clusters, c_x is the centroid of cluster σ_x is the average distance of all elements in cluster x to centroid c_x, and $d(c_i, c_j)$ is the distance between centroids c_i and c_j. Since algorithms that produce clusters with low intra-cluster distances (high intra-cluster similarity) and high inter-cluster distances (low inter-cluster similarity) will have a low Davies–Bouldin index, the clustering algorithm that produces a collection of clusters with the smallest Davies–Bouldin index is considered the best algorithm based on this criterion.

- The *Dunn index* aims to identify dense and well-separated clusters. It is defined as the ratio between the minimal inter-cluster distance to maximal intra-cluster distance. For each cluster partition, the Dunn index can be calculated by the following formula:[35]

$$D = \frac{\min_{1 \leq i < j \leq n} d(i, j)}{\max_{1 \leq k \leq n} d'(k)} \tag{2.2}$$

  where $d(i, j)$ represents the distance between clusters i and j, and $d'(k)$ measures the intra-cluster distance of cluster k. The inter-cluster distance $d(i, j)$ between two clusters may be any number of distance measures, such as the distance between the centroids of the clusters. Similarly, the intra-cluster distance $d'(k)$ may be measured in a variety ways, such as the maximal distance between any pair of elements in cluster k. Since internal criterion seek clusters with high intra-cluster similarity and low inter-cluster similarity, algorithms that produce clusters with high Dunn index are more desirable.

- The *silhouette coefficient* contrasts the average distance to elements in the same cluster with the average distance to elements in other clusters. Objects with a high silhouette value are considered well clustered, objects with a low value may be outliers. This index works well with k-means clustering, and is also used to determine the optimal number of clusters.

2.6 Isee Systems - STELLA

The isee systems is a leading developer and manufacturer of *systems thinking* and dynamic modeling software. Founded in 1985 by renowned systems thinking practitioner Barry Richmond, isee systems has grown to be a thriving company with substantial global reach in a variety of markets. They continually strive to bring the best dynamic modeling software to their customers by developing new functionality, implementing customer requests, and consistently pushing the envelope on our technology.

In 1989, Barry Richmond (and isee systems) was awarded the Jay Wright Forrester Award by the System Dynamics Society for being the first to introduce an icon-based model building and simulation tool, Stella. Stella brought computer simulation-based model building to the mass market. In 1990, isee systems introduced iThink for business simulation. isee systems also created the first Management Flight Simulator in 1991, pioneered the introduction of the first Learning Environment in 1995, and delivered the first conversational systems thinking workshop in 1999. In 1999, isee systems also introduced isee NetSim, the first system to deliver management flight simulators on the web. isee NetSim was expanded to multiplayer in 2002 and completely redesigned to generate Wysiswyg web applications from Stella and iThink interfaces in 2007. 2007 is also the year isee systems committed to the draft Xmile standard for model interchange, releasing the first Xmile-compatible product in 2012. In 2015, we unveiled the next generation of dynamic modeling software, Stella Professional, which allows real time analytics with Stella Live!.

The isee systems dynamic modeling software is a powerful tool that allows the user to create system diagrams that can be simulated over time. By creating these diagrams, the ability to understand the behavior of a system and identify areas for improvement. The ability to simulate over time allows the user to easily test several hypotheses to avoid unintended consequences and costly trial and error. With an intuitive user interface and effective analytic our software allows you to quickly advance your modeling skills. They offer a wide range of services such as online courses from beginner to advanced, in-person workshops, one-on-one modeling support, as well as many free webinars and tutorials.

Barry Richmond believed that as a population, their methods of thinking and communicating were outdated, making it difficult to solve the major issues of the world. They propose to change the way we think, communicate, and teach as a solution. This new dynamic way of thinking, called Systems Thinking, enables people to build a better understanding of the world around them, so that they make better decisions. Isee systems is dedicated to continuing this effort to change the way we think by bringing *systems thinking* to the world. They strive to create intuitive, easy-to-use dynamic modeling software that makes Systems Thinking accessible to everyone, from beginner to expert. As people continue to use systems thinking every day, they will be better able to understand dynamic relationships within a system, think through a problem, and communicate their ideas and solutions more proficiently.

Systems thinking is a disciplined way of understanding dynamic relationships that enables you to make better choices and avoid unintended consequences. Through systems thinking, a practitioner will have a better understanding of the interdependent components that create a system and be able to identify the leverage points for effective intervention.

As they mention, building mental models is something we all do everyday and our brains are so good at it. Simply put, mental models are abstractions of reality that we create and simulate to help make meaning out of experiences and help us come to decisions that inform our actions. While building mental models about everything, research shows that there is not always good to understand the implications of the mental models. By building a computer model that matches the mental model, we are able to run simulations to see what the outcomes would be over time. In particular, this helps us understand how both feedback and action at a distance can lead to unexpected results.

Armed with a computer model, we can analyze the behavior of the system under different scenarios. This helps us understand the most likely paths the system will take in the future. The proposed model can be use as a decision-support tool, testing different policies that we believe will ameliorate the problems we are facing, to find which policies are effective. This kind of model to help the decision making process is the one we are proposed in terms to determine a variety of solution in the ready-mixed concrete delivery problem.

2.7 Literature Review

The ready-mixed concrete delivery problem is a complex assignment problem widely studied. Some studies that provide insight about the concrete delivery process are Chua and Li [4], Dunlop and Smith [5], Lu et al. [19, 21], Maghrebi et al. [23, 30, 31], Smith [43], Wang et al. [48], Zayed and Halpin [54].

Several attempts have been made to formulate the mathematical model. One common approach is to model the problem as a special case of vehicle routing problem [2, 35], nevertheless there are important differences between that problem and ready-mixed concrete that must be taken into the account. First, a truck can only supply concrete to one customer on each trip, whereas in vehicle routing problem a truck normally can supply more than one customer. Second, the concrete cannot be hauled for a long time because fresh concrete is a perishable material. Because these differences, a set of new constraints must be added to the original vehicle routing problem formulation [1, 6, 10, 13, 27, 28, 35, 40, 51].

Proper dispatch at ready-mixed concrete plants could greatly benefit the plant and construction sites in terms of both efficiency and effectiveness. However, in practice, dispatch is often accomplished individually for production and delivery. In this study, an integrated mode of production and delivery is proposed and discussed that will lead to lower operation costs for ready-mixed concrete plants. Scheduling studies for ready-mixed concrete production and delivery have been conducted for several years. Most of these studies consider some of the restrictions that are involved in real situations, and few have considered the integrated scheduling of both production and delivery. Compared to these prior studies, this paper, however, focuses more on the integrated scheduling of production and delivery of pumps and trucks and considers more practical elements, such as waiting time between vehicles and construction sites and continuity of work in construction sites, to provide an effective method for improving efficiency as well as saving costs.

Regardless the techniques solution, we can find in the literature the use of exact methods such as *benders decomposition* [25] and *column generation* [26, 32]. Yan et al. [51] introduced a numerical method for solving the ready-mixed concrete optimization problem by cutting the solution space and incorporating the *branch* *and bound technique* and the linear programming method. Yan et al. [53] used decomposition and *relaxation techniques* coupled with a mathematical solver. It can also be found works that combine mathematical formulation with the dependence on human expertise [10, 14, 24, 34]. Maghrebi, Waller, and Sammut [33] attempt to solve the ready-mixed concrete delivery problem automatically by anticipate human decisions through *machine learning techniques*. The issue in this approach is the quality of the experts decisions.

Despite significant progress on ready-mixed concrete delivery problem in the last two decades, the research has indicated the inefficiency of mathematical models to achive optimallity, mainly because the large number of variables, the uncertain and dynamic data involved in real situations [24]. Moreover the problem has been proven to be $\mathcal{NP}$-hard by Asbach, Dorndorf, and Pesch [1], Maghrebi, Sammut, and Waller [23], Maghrebi, Waller, and Sammut [24], Yan, Lai, and Chen [51], for which obtaining the exact solution for large scale ready-mixed concrete delivery problem is computationally intractable with available computing facilities [40, 48, 50, 52].

To overcome this issue, a wide range of heuristic methods have been used in the literature such as *genetic algorithms* [9, 10, 19, 24, 29, 36], *particle swarm optimization* [15, 20, 49], *bee colony optimization* [44], *tabu search* [44], and *variable neighborhood search* [1]. Also, Maghrebi et al. [24] presented an evolutionary based method which can solve the ready-mixed concrete delivery problem without needing any additional algorithm. They developed a sequential meta-heuristic method which is ten times faster than their previous method and rather than direct travel costs can also minimize the number of fleets. Liu et al. [16] introduced an integrated framework for solving both production and delivery of ready-mixed concrete. Chou and Ongkowijoyo [3] present a decision aid model for selecting the on-site ready-mixed concrete type based on a reliability assessment process. Zhang and Zeng

Table 2.1: Comparison of literature for the ready-mixed concrete delivery problem.

Year	**Reference**	**Allocation order-plant**	**Allocation order-truck**	**Staff scheduling**	**Overbooking**	**Special orders**	**Logistic aspects**	**Business analytics**	**Adaptable programming**
2017	**Present work**	✓	✓	✓	✓	✓	✓	✓	✓
2016	Maghrebi et al. [33]	✓	✓	-	-	-	-	-	-
2016	Ghasri et al. [11]	✓	✓	-	-	-	✓	-	-
2015	Maghrebi et al. [32]	✓	✓	-	-	-	✓	-	-
2015	Maghrebi et al. [30]	✓	✓	-	-	-	-	-	-
2015	Maghrebi et al. [31]	✓	✓	-	-	-	✓	-	-
2014	Maghrebi et al. [26]	✓	✓	-	-	-	✓	-	-
2014	Maghrebi et al. [29]	✓	✓	-	-	-	✓	-	-
2014	Liu et al. [16]	-	✓	-	-	-	✓	-	✓
2014	Kinable et al. [13]	✓	✓	-	-	-	✓	-	-
2014	Hanif and Holvoet [12]	✓	✓	-	-	-	✓	-	✓
2013	Maghrebi et al. [24]	✓	✓	-	-	-	-	-	-
2012	Yan et al. [53]	✓	✓	-	-	-	✓	-	-
2011	Yan et al. [52]	✓	✓	-	-	-	✓	-	-
2011	Park et al. [38]	✓	✓	-	-	-	✓	-	-

[55] integrated an intelligent monitoring system with a hybrid heuristic algorithm to more effectively reschedule ready-mixed concrete delivery problem when customers demands are assumed to be dynamic.

Different methods have been tried to solve the ready-mixed concrete delivery problem, regarding of the different studies the practical solutions are null and the solution continues to be handled by experts. From the scientific point of view, finding the optimal solution of the ready-mixed concrete delivery problem (i.e., provide the feasible solution at the least possible cost) is desirable, but in practice, the main objective is to efficiently supply all customers whilst the profitability of the company improves. Usually, there are two parts of interest: the customer service (on-time delivery) and the assign between plants and customer, but both decisions comes with the challenge of the number of plant allocation, number of clients, and amount of available truck, among others.

To our knowledge and based on the literature presented, the only work that capture the whole process of concrete delivery is the one proposed by Durbin [6]. Therefore, we took some ideas as a basis to construct our solution but instead of using mathematical models and solved using solvers we use a dynamic tool that capture in more realistic way the process and add new functionalities to the dispatchers, planners, and operators. In their work, they embedded its ATP model in trucks and customer demand based the input in the decision expert. The expert selects how many trucks each plant needs to attend customer demand to achieve global feasibility. Our hypothesis is that rely on expert's decision for this process can generate a suboptimal capacity of trucks in concrete plants, that is the company demand is unbalanced in terms of trucks. The combinations of characteristics to one expert is overpass therefore, companies need more than one expert to attend this issue. The companies split the demand in counties and each expert is assigned to one county. Therefore, the ATP is an essential process

We overcome this problem knowing that trucks are the scares resource of any concrete company and the core of the performance of real time operation is the first round. Our approach takes advantage of the location of the demand and runs an algorithm based on a mathematical formulation to detect how many trucks is needed in each plant. The details of the implementations are presented in the next section.

The desire of the companies is that the ready-mixed concrete delivery process becomes automated to control the critical demand for concrete but still a human resource is needed, due to the complexity of the problem the experts need to consider a lot of variables in order to achieve good results. Therefore, in this study we introduce tool to re-assign the whole delivery schedule of a region. Also, the tool includes real-time monitoring to easily detect when the trucks are delayed or queued in plants, customer sites, and in their travel. These considerations are needed to make better decisions in the ready-mixed concrete delivery.

Chapter 3

Problem Description

In this chapter, we explain the process, the complexities, and the irregularities of the daily ready-mixed concrete delivery problem. Therefore, an introduction to ready-mixed concrete delivery is leading into a discussion of the main elements, *process description*, *dynamic environment*, *real-time issues*, *overbooking*, and *data accuracy.*

3.1 Main Elements

There are five main elements involved in the ready-mixed concrete delivery problem *concrete*, *orders*, *trucks*, *pumps*, and *plants.* In the following lines it is described an explanation for each of these elements stressing their characteristics and limitations.

Concrete : The concrete is a *perishable* product, it needs to be poured in a continuous way and it only has approximately one and a half hour after preparation, before its hardens on the truck. The concrete is also characterized by high variability in its demand caused by errors in the planning of the customers or bad weather, which causes cancellation of orders.

Orders : When a customer makes an *order*, the specifications of concrete are proportioned. Some of them are: quantity, strength, viscosity, or combinations of materials. If the amount of concrete requested by a single customer exceeds the capacity of a single truck, multiple deliveries are required, these are called *services*. Services for the same customer cannot overlap in time and have to take a maximum time lag into consideration; the time between two consecutive services is limited to guarantee proper bonding between the two layers of concrete. Deliveries may not be preempted or split among multiple customers. The time required to perform a delivery is truck dependent. Sometimes, the customer needs an addition amount of concrete to its initial amount this impact the original schedule of the plant as extra request of concrete from the customer requires to send one or more trucks. These characteristics affect the decision of the order of service for each plant. Not all the plants have the same technology to perform specific mixtures or the materials needed for a particular order. Another consideration, is that the plant that makes the first load to a construction site must supply the entire order to maintain consistency i.e., architectural reasons and concrete properties. These orders are called *single-source orders*.

Trucks : Ready-mixed concrete production requires delivery by *trucks* to each construction site, with planned delivery routes. In addition, to delivering the concrete, trucks need to perform a continuous agitation of the mixture during the delivery to avoid hardness and be able to pouring at the construction sites. Good planning of these processes can enhance quality control and increase production efficiency of the concrete. Trucks represent a limiting factor because there is a maximum number of trucks available at each plant, with also, a maximum capacity. The capacity of each truck is specified in eight cubic meters of concrete but for safety reasons, only seven cubic meters are loaded. Usually, as an order requires more than one service, a sequential arrival of trucks at customer sites is needed an may. Typically, the frequency of arrival is requested by the customer. Trucks are tied together with drivers, therefore the delivery of concrete to a customer is delayed until a truck and a driver are available. Drivers also have restrictions, these are on their working day, such as a maximum daily hours worked and the minimum amount of hours between working days.

PUMPS : Some orders require *pumps* assist concrete unloading and casting work. The pumps should arrive at the construction site no later than the first truck and may not depart until the site order is completely satisfied. After finishing the task of one site, a pump may leave for the next construction site without returning to the plant but must return to the plant after all tasks are accomplished for the day.

PLANTS : The *plant* has a maximum production and truck-load capacity per hour. The plant can only produce one load per time. Usually, the loading time is between ten and twenty minutes, depending on the plant machinery and technology. The concrete costs change for each plant, since there are different materials, suppliers (production cost), and different locations from customers (traveling cost).

Once each of the main elements is described we proceed to explain the stages for the ready-mixed concrete delivery process. These stages are *offer enable*, *order taking*, *order scheduling*, *dispatching*, and *delivering*. To illustrate all the stages a diagram is presented in Figure Figure 3.1.

OFFER ENABLE: For an operational day, the company offers a number of available slots for customers to meet its delivery requirements. There are limitations that depend on the available resources (plants, trucks, and personal) to offer these slots, and are considered in this stage.

Order taking : In the company under study, the dispatch of concrete is based on *orders* from *customers* which may have more than one *construction sites* to be attended. Therefore, the company take orders from customers through a Service Call Center. The days in advance for a customer to make an order depend if the customer has a priority according to its historical data. The days in advance to take an order variate from seven to one day. When an order is received, each customer indicates the quantity and specific features of concrete. One order may result in more than one *service*. If the quantity of concrete ordered overpass the capacity of a truck (7 m^3), the order splits into several services in order to fulfill the amount required for the customer. According to these specifications, the production planners and managers have to decide if a new order is accepted or not. If the order is not accepted, the company offers an alternative hour or day to satisfy the customer preference whenever it is possible. Once orders are confirmed and scheduled, the next step (order scheduling) begins. This stage happen on daily operations.

Order Scheduling : Before the operation starts, each ready-mixed concrete plant prepares the production facilities (mixing raw materials) and the vehicle deliveries (trucks, pumps, and drivers) according to the schedule. An illustation of the step is shown in Figure 3.2.

Dispatching : In order to explain the ready-mix concrete delivery, the process is separated in three time windows called *rounds*. The first round begins at 8:00 a.m.(begin of the operation) and ends at 11:00 a.m.(return of first delivery trucks to plants). The second round begins at 11:00 a.m.and ends at 2:00 p.m.The third round begins at 2:00 p.m.and ends at 5:00 p.m.Other considerations are that the available trucks in a plant are idle until an order (or service) is assigned to them. The *dispatchers* decide the assignments of plants and trucks to attend customers according to the schedule to arrive on time. Daily operations of dispatchers become difficult as they need to select from several alternatives to continuously supply concrete to each of the customers scheduled. The considerations to assign can be categorized into three types: *order specifications*, *truck cycle time*, and *plant limitations*. Within the specifications of the orders are: quantity (cubic meters), technical characteristics of the concrete, first service scheduling hour, and *frequency* (time window between each service from an order as requested by customers). The fulfillment of the frequency is key to a continuous delivery (download and unload) that guarantees the quality of the construction project. The route of the trucks is defined by the distance between plant and customers, the drivers availability, and the *cycle time*. The cycle time includes the time of customers preparation, the construction-site preparation, the concrete unloading, the trucks cleaning, and the traveling time to return to the plant. Regarding the limitations of the plant, it is known which type of concrete is produced in each plant and the maximum capacity of concrete production per hour. Based on these considerations, the dispatcher has the challenge to assign trucks to each customer in order to deliver (next step) on time. The challenge increases dramatically as several active ready-mixed concrete plants on different locations are able to supply each customer, a considerable number of customers need to be attend at the same time, and there are several trucks to select and send to the loading area in each of the plants. The role of the dispatchers becomes crucial to the company since the day-on-day schedule of the ready-mixed concrete delivery problem depends on them. After the dispatchers assign a truck for a service, fresh concrete with the characteristics requested is loaded into a truck. Then, the truck moves below the discharge area of a loader at the plant. During this process, the loader perform a well mixture of the concrete ingredients to drop the fresh concrete into the truck. Next, the driver washes the truck and inspects if the material is located properly inside the body of the truck, if there is any residual the driver push it into the body of the truck with a stream of water. After that, the driver checks the quality of the material and removes any concrete left in the exterior of the truck for safety reasons. Finally, the truck is ready to deliver concrete to the customer.

Delivering : After the driver leaves the plant, the driver starts traveling to its assigned construction site. When the driver arrives, assuming that the customer is ready for receiving the concrete, the truck is positioned in the *pouring* (also called *unloading* and *placing*) location. Later on, the truck unload concrete until there is no concrete left. Then, the driver moves from the pouring location and wash the truck to remove any residue that may solidify into the truck. Once the delivery of concrete is done, the driver returns to a plant (not necessarily the same as the starting plant) in order to be available to a new assignment or quit its labor day.

3.2 Dynamic Environment

There are many aspects (or events) that cause dynamism and uncertainty in the concrete industry. The ones that we consider the most relevant are enlisted next as customer-created problems, operating cost, traveling time, and breakdowns.

Customer-created problems: There are customer-created problems that increase the cost of delivering concrete and impact the efficiency of the delivery process, therefore the customer has greater influence over the ready-mixed concrete supply process, even greater than the supplier [42]. The main common customer problems are: preparation, incorrect order, delays, and cancellations. The customers may not be prepared when the truck arrives to unload the concrete. These scenarios result in truck usage delay, affecting next deliveries, or may stop the dispatching of additional services for that customer until the preparation is corrected. Nevertheless, some customers are very optimistic about their ability to unload trucks but as the company have their historical behaviours, with high probability the time extends more that expected. Also, the customers seldom knows the exact amount of concrete needed for a specific order. Underestimating as little as one cubic meter could require an additional trip from either a truck already assigned to a customer site or another available truck. For this reason, it is often the case that the truck or trucks that are sent to deliver the additional concrete are diverted from delivering to another customer. The more that the customer underestimates, the greater the impact on the ability of servicing on time other customers. Conversely, if a customer overestimates the amount of concrete and abruptly decreases the ordered amount after delivery has started, the company may be left with idle trucks or may be left with trucks at the wrong plants to quickly assign to other jobs. Another issue to consider is when the customer delays or cancels an order right before trucks were assigned according to scheduled and it starts to travel from the plant to the customer.

Operating Costs: Increases in costs occur due to keep drivers and trucks out for a longer period of time than necessary. The inability of the company to use trucks from other near customer sites when there is a delay of current assigned customers results in an increasing cost to not use with efficiency the available resources. These costs and the ones from the cost to attend the issues mention previously have a significant impact on the profitability of the company. Therefore, the ability to assess the current states of all deliveries, to determine if the delivery is on-schedule or delayed, and to respond appropriately can provide significant cost savings to the company. Moreover, when delivery of concrete is smooth, contractors in construction sites does not worry about trucks idling on site waiting to unload the concrete. Therefore, ready-mixed concrete dispatchers has the challenge to deliver concrete in a timely and cost-effective manner.

Traveling time: Other important factor that affect the dynamics in this industry is the traveling time from a plant to a customer site and viceversa. On daily operation, differs on the zones where the construction site as the traffic variates according to the hour and the weekly day. Thus, the coordination of the entire fleet at scheduled time, on a specific day, become difficult to ensure the on-time concrete delivery for each of the customer sites.

Weather: Weather impact directly on the concrete delivery process. The expected travel-time increases when inclement weather occurs causing delays in arrivals on construction sites. Additionally, concrete need certain weather conditions to be delivered, being nearly impossible to deliver when appear heavy rain or cold temperatures.

Breakdowns: Another factor is the breakdown of either trucks or plants. The breakdown of an empty truck can result in delivery delays until the truck is brought back into service, or until the driver is placed into a backup truck. The breakdown of a loaded truck has additional cost associated with material replacement; late delivery to the customer and removal of hardened product from the drum of the truck. The breakdown of a plant can create a significant disruption in the delivery plan for the entire company. When this occurs, the company is mainly interested in system recovery and places priority on continuing any customer delivery that is currently in progress.

3.3 Real-time Issues

Ready-mixed concrete delivery performance is also heavily influenced by factors that are under the company's control. One of the most complex issues encountered in this research deals with the effects of real-time implications on the mathematical solutions that are generated.

The most significant issue is the determination of proper reaction to events that have not occurred as anticipated. When this transpires, there is often a domino effect on the schedule. For example, the decision to direct trucks from a later job to finish a current job causes problems for the later job, which create further delays. Both loads in progress and loads scheduled to occur later are impacted.

A second problem is that the data changes significantly while the solution is being calculated. For example, in the time interval between the data snapshot and schedule completion, a truck is placed in "shop" status (meaning that it needs some mechanical adjustments and is unavailable for an unknown amount of time). The schedule likely made use of this truck, and until the problem is re-solved, the schedule will be inaccurate. As a result, the solution generated is out-dated before it can be used. Hitting this moving target is challenging, but the process is addressed in creative ways as described in the following chapters.

An example of some real-issues is illustrated in Figure 3.3. In this example four Jobsites have real-time issues that permit the customer to add new valume of concrete (Jobsite 1), delay their stablished delivery schedules (Jobsite 2 and 3), or cancel all their services (Jobsite 4). Only one service in one Jobsite arrive on time in this example (second service of Jobsite 3).

3.4 Overbooking

In the same way as other different enterprises, the concrete business works with overbooking. This is done in light of historical rates of cancellations and postpones that happen each day. At the point when client postponements or retracts are lower than anticipated, overbooking makes uncommon dispatching difficulties. At the point when this happens, the activity plans can be one of the accompanying other options

1. The first option accessible is deferring the beginning season of the conveyance, called *slipping* the request. The measure of the postponement is reliant upon truck accessibility, the particular subtleties of the request (a more huge effect is produced by deferring a huge request), and the significance of the client. Slipping the request is particularly valuable if there is just a brief deficit in trucks that can be made up later in the day when request decreases.

2. A second option is to build the between appearance pace of the trucks, called *stretching* the request. This spreads out the conveyance throughout a more extended timeframe. The effect of this is that less trucks are utilized at any one point on schedule to meet the conveyance prerequisites of a client, yet the trucks are being used for a more drawn out timeframe. The result is called *squeezing the balloon* (on the grounds that the truck utilization related with the request is packed in one time period and extends in some other time period). Extending orders is valuable if there is a reliable deficiency (a consequence of overbooking) for the duration of the day.

3. A third option is to acquire trucks from another organization. Related organizations regularly work in a similar geographic region. If so, the organizations may share trucks to aid conveyance prerequisites. This choice can address either a transient lack of trucks or a predictable deficiency of trucks.

4. At the point when any remaining options have been endeavored and the solid organization actually experiences issues meeting conveyance necessities, the

last option is to advise the client and drop the request. This is just done if all else fails.

A few clients perceive the test in conveying concrete. Therefore, on a few positions these clients not just give a mentioned conveyance time, they likewise give the most recent time that the client will acknowledge conveyance, a drop-dead time.

The initial two choices are executed on the fly by the dispatchers. Getting trucks is an alternative that isn't accessible to all organizations and obviously, it's anything but an industry standard. The last option is to drop a request, in spite of the fact that it's anything but a favored alternative for evident reasons.

3.5 Accuracy of Data

One of the significant reasons that this decision-support system has been effectively actualized is that the organization has planned an information base framework and has the two GPS gear and on-board sensors to catch a large part of the required information. Nonetheless, perceive that the caught information ordinarily has mistakes, because of elements like the accompanying:

- The sensor on board the vehicle doesn't work as expected and the situation with the truck is accounted for mistakenly.
- The Gps receiver, or specialized gadget in the vehicle doesn't work as expected, bringing about off base information transmission or an absence of information inside and out.

- The client site has no a decent gathering, bringing about a postponement in information transmission.
- The driver doesn't react to a movement order and in this manner reports to some unacceptable plant.
- The driver dumps a segment of the heap, at that point moves the truck (setting the truck in an "end-pour" state) to another area and keeps on pouring cement.

The best method to react to wrong information is to connect with the dispatchers in the issue. The dispatchers track the trucks and orders by means of a graphical User Interface. At the point when they notice an expected issue, they speak with the drivers by radio and decide whether there is a conveyance or an information issue. On the off chance that there is a conveyance issue, the dispatcher can defer the remainder of the conveyances to this client. In the event that there is an information issue, the dispatcher physically refreshes the information inside the data set. Whenever the solver is run, the more precise information will be utilized.

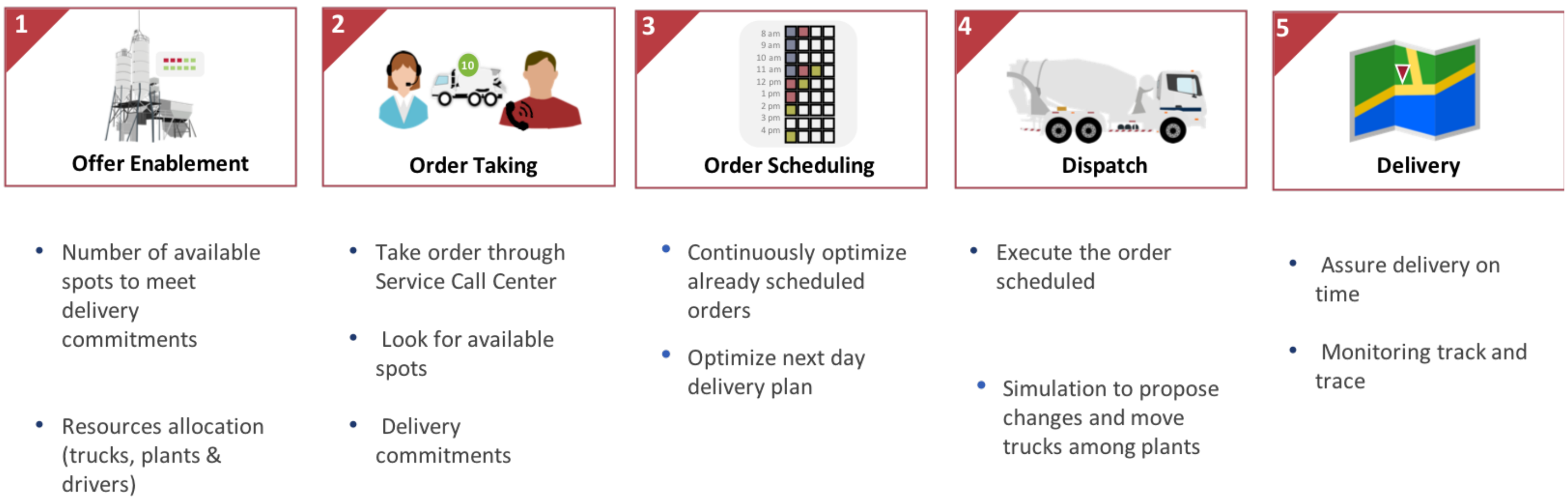


Figure 3.1: Diagram of the ready-mixed concrete delivery problem.

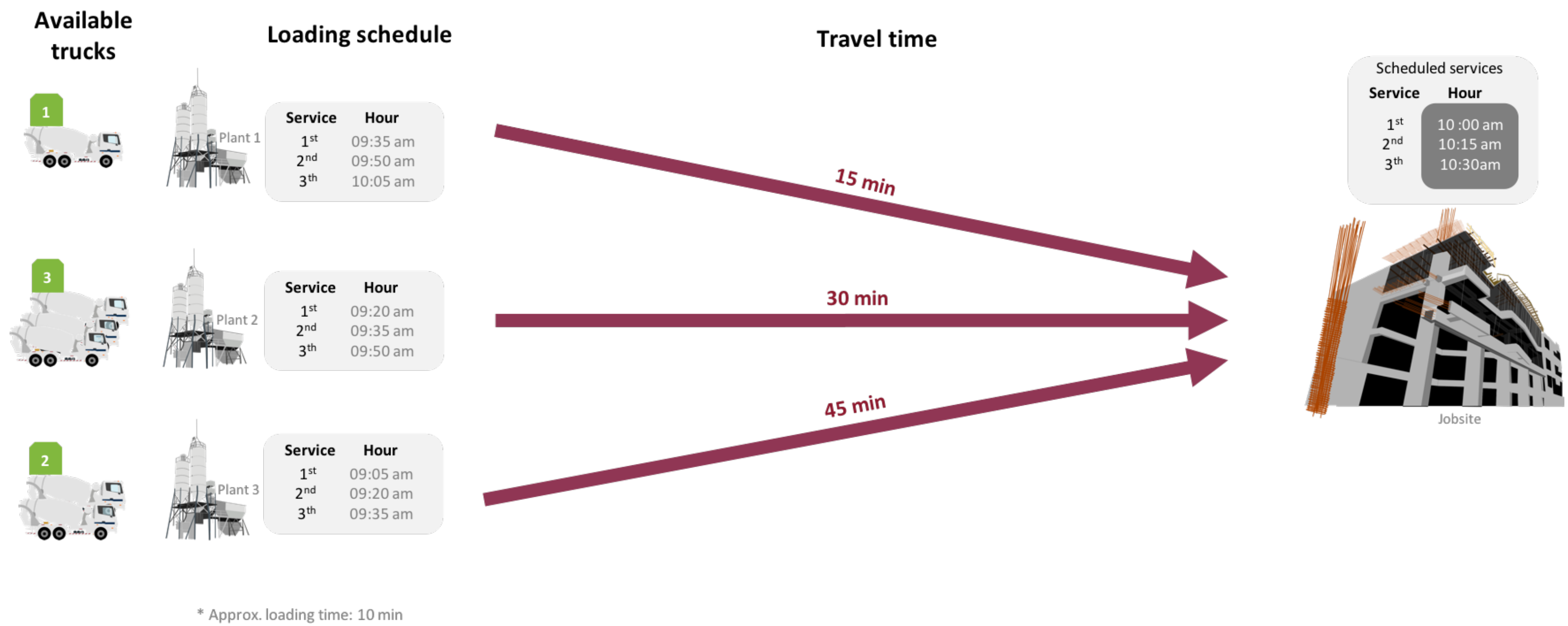


Figure 3.2: Example of the decisions to perform an order scheduling.

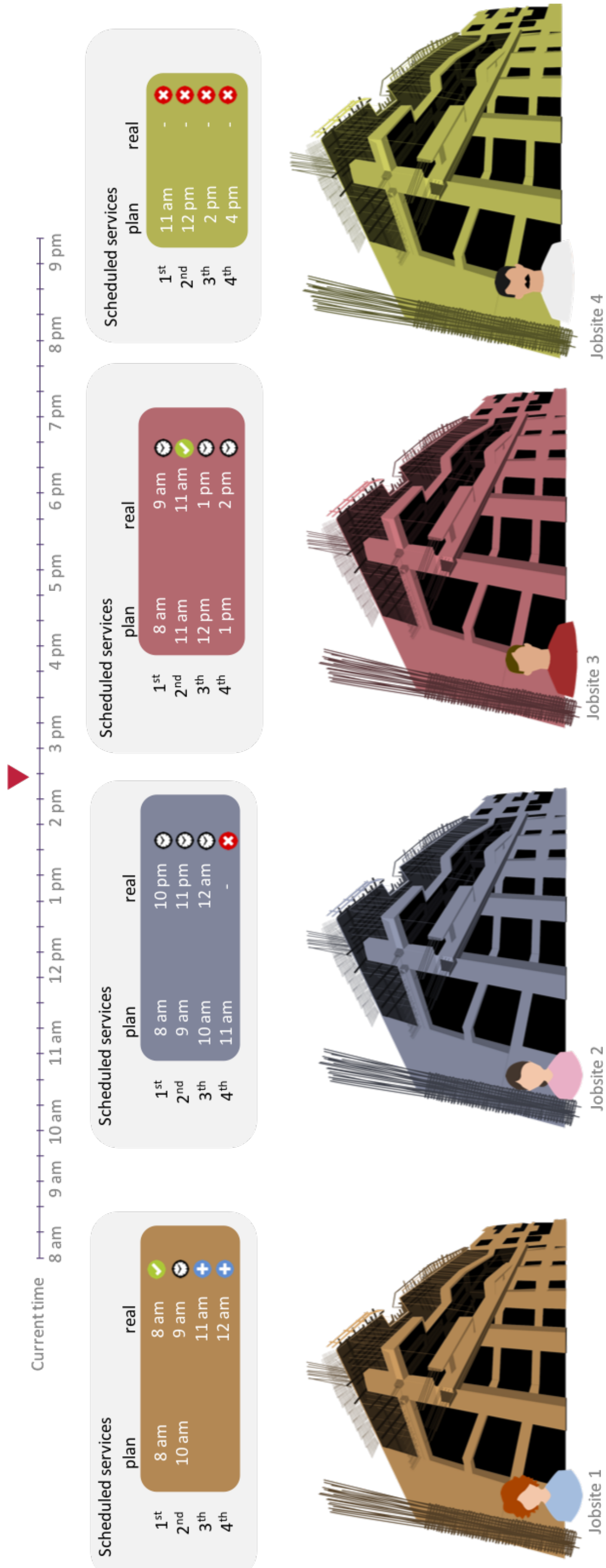


Figure 3.3: Example of real-time daily issues in four Jobsites.

Chapter 4

Methodology

This chapter begins with a discussion on data collection/storage issues and travel time data. This is followed by a discussion of the truck-based dispatching elements of the decision-support tool: the order entry planner and arrival time planner. Both of these modules are used in planning activities at least one day in advance. The chapter concludes with a discussion of the demand dispatching elements of the decision-support tool: the next day planner, the real-time planner, and the real-time dispatcher. These modules are used for real-time operational dispatching and re-scheduling. Included in these discussions are references to the many adaptations that are required to implement a decision-support tool in a dynamic environment with real-time requirements.

4.1 System Dynamics

The behavior of a system arises from its structure, that structure consists of the feedback loops, stocks and flows, and nonlinearities created by the interaction of the physical and institutional structure of the system with the decision-making processes of the agents acting within it [45].

4.1.1 Fundamental Modes of Dynamic Behavior

Change takes many forms, and the variety of dynamics around us is astounding. The most fundamental modes of behavior are exponential growth, goal seeking, and oscillation. Each of these is generated by a simple feedback structure: growth arises from positive feedback, goal seeking arises from negative feedback, and oscillation arises from negative feedback with time delays in the loop. Other common modes of behavior, including S-shaped growth, S-shaped growth with overshoot and oscillation, and overshoot and collapse, arise from nonlinear interactions of the fundamental feedback structures.

4.1.2 Exponential Growth

Exponential growth arises from positive (self-reinforcing) feedback. The larger the quantity, the greater its net increase, further augmenting the quantity and leading to ever-faster growth. Pure exponential growth has the remarkable property that the doubling time is constant: the state of the system doubles in a fixed period of time, no matter how large. It takes the same length of time to grow from one unit to two as it does to grow from one million to two million. This property is a direct consequence of positive feedback: the net increase rate depends on the size of the state of the system. Positive feedback need not always generate growth. It can also create self-reinforcing decline. By other hand, linear growth is actually quite rare. Linear growth requires that there be no feedback from the state of the system to the net increase rate, because the net increase remains constant even as the state of the system changes. What appears to be linear growth is often actually exponential, but viewed over a time horizon too short to observe the acceleration. Growth is never perfectly smooth (due to variations in the fractional growth rates, cycles, and perturbations), but in each case exponential growth is the dominant mode of behavior.

Process Point: When a Rate Is Not a Rate In dynamic modeling, the term "rate" generally refers to the absolute rate of change in a quantity. The population growth example above states, "the larger the population, the greater the birth rate." The term "birth rate" here refers to the number of people born per time period. Often, however, the term "rate" is used as shorthand for the fractional rate of change of a variable. Similarly, we commonly speak of the interest rate or the unemployment rate. The word "rate" in these cases actually means "ratio": the interest rate is the ratio of the interest payments you must make each period to the principal outstanding; the unemployment rate is the ratio of the number of unemployed workers to the labor force.

4.1.3 Goal Seeking

Positive feedback loops generate growth, amplify deviations, and reinforce change. Negative loops seek balance, equilibrium, and stasis. Negative feedback loops act to bring the state of the system in line with a goal or desired state. They counteract any disturbances that move the state of the system away from the goal. If there is a discrepancy between the desired and actual state, corrective action is initiated to bring the state of the system back in line with the goal. Every negative loop includes a process to compare the desired and actual conditions and take corrective action. Sometimes the desired state of the system and corrective action are explicit and under the control of a decision maker. Sometimes the goal is implicit and not under conscious control, or under the control of human agency at all. In most cases, the rate at which the state of the system approaches its goal diminishes as the discrepancy falls. We do not often observe a constant rate of approach that suddenly stops just as the goal is reached. The gradual approach arises because large gaps between desired and actual states tend to generate large responses, while small gaps tend to elicit small responses. When the relationship between the size of the gap and the corrective action is linear, the rate of adjustment is exactly proportional to the size of the gap and the resulting goal-seeking behavior is exponential decay. As the gap falls, so too does the adjustment rate. And just as exponential growth is characterized by its doubling time, pure exponential decay is characterized by its halflife-the time it takes for half the remaining gap to be eliminated.

4.1.4 Oscillation

Oscillation is the third fundamental mode of behavior observed in dynamic systems. Like goal-seeking behavior, oscillations are caused by negative feedback loops. The state of the system is compared to its goal, and corrective actions are taken to eliminate any discrepancies. In an oscillatory system, the state of the system constantly overshoots its goal or equilibrium state, reverses, then undershoots, and so on. The overshooting arises from the presence of significant time delays in the negative loop. The time delays cause corrective actions to continue even after the state of the system reaches its goal, forcing the system to adjust too much, and triggering a new correction in the opposite direction.

4.2 Dynamic Planning Model

In this section, we detail, as far the confidentiality permits, the main concepts regarding the implementation of each of the research tools. For each tool, the relevant concepts, considerations, and necessary parameters will be detailed. For the dynamic planning tool, input variables, process rules, and characteristics are specified. For the monitoring tool in real time, the features and considerations are presented.

Based on the problem description in Chapter 3, the elements and principal characteristics are presented in the diagram of Figure 4.1. There are two main parts in this diagram, the productivity (profits) and the compliance (customer satisfaction). This two parts are related to two relevant variables of the company: profits and quantity of orders. The relationship is that higher the productivity, higher the profits and lower compliance, lower the quantity of orders to be served.

If we focus in productivity, there is an offer enable that assign a quantity of orders. This orders are reflected if there is a decreasing value in the optimal origin. To decrease optimal origin also affects negatively to productivity and decrease the number of resources available. When this occurs, trucks need to be removed and some plants need to be closed as there is no longer profitable to the company business. Also, this generates a cycle where there is less offer enable and therefore less quantity of orders by the costumers. But since there are fewer orders, now the optimal origin may be satisfying increasing the company productivity and increasing the resources, yielding more offer enable. It looks like a system balanced by supply and demand.

If we focus in the compliance, the system is stagnant (regulated) as higher quantity of orders decreases the optimal origin making the compliance to be reduced. Fewer quantity of orders permits to perform a better truck assignment what increases compliance and therefore, higher quantity of orders. This higher quantity of orders difficult the balance of trucks, therefore the compliance decreases and the orders are reduced. As the orders are reduced, now the balance of trucks is better, that increase the compliance and generate much more quantity of orders, this starts the cycle again.

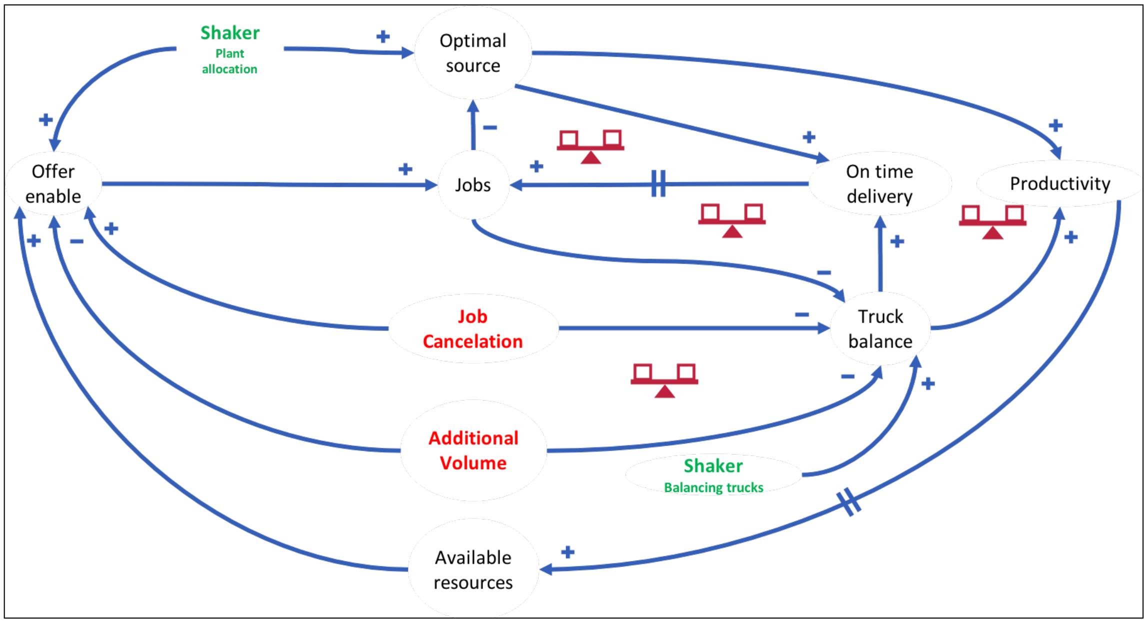


Figure 4.1: Diagram of causality for ready-mixed concrete delivery problem.

The dynamic model result counteracts the fact that greater quantity of orders impacts in a better optimal origin, therefore the productivity increases, and needing more trucks and more orders (supply). This permits the system to enter into a virtuous cycle. Nevertheless, before cancellations come into play, the system is in perfect balance. However when cancellations appear, the truck balance decreases, which lowers productivity and causes everything to decrease (bottom part in the diagram). Also, cancellations increase the offer enable yielding more quantity of orders to serve. Another variable that affects is the additional volume requested by the customers, this decrease offer enable, and as we explain previously affects the productivity. These two external interaction of the process affect the removal of trucks or the surplus of trucks at each plant.

Considering the diagram, the dynamic model is presented. The model for decision support has been developed using Stela Architect through Isee PLayer, allowing to incorporate in detail the systems dynamics model.

Consistency on what is modeled and simulated against reality was checked based on years of experience of people and literature reviews. Robustness on how model structures were implemented to produce expected behaviors was exhaustively reviewed equation by equation in order to check the best way to implement modeled processes. Implemented structures produce general behaviors that can be customized based on data files from GINCO to consider the different characteristics:

- Standardized logic-discrete structures were incorporated after a process of enquiry, discovery, and standardization of structures.
- Redundancies, obsolete structures, and structures without value for current usage were eliminated (reference to enquiry system).
- Sectors (I-THINK feature to run isolated model fragments for testing) were assigned to every function of the model. Firstly, functions were identified, explicitly defined, and corresponding input and output variable were explicitly declared. So the model can be understood by functions and tested by sectors.
- Rename of the 95% of the variables was carried out to enable the communication of the knowledge about the process by looking at the graphical model itself.
- Balance between computational efficiency and communication efficacy of the graphical model is a main characteristic of the current of SIMUL V2©.

There are four objectives to achieve: (1) to anticipate potential operational breaks, (2) to identify the best plant to deliver each service, (3) to enable a planner/dispatcher to undertake corrective actions in order to ensure the timely fulfillment of orders, and to transfer knowledge gathered by years on the concrete order fulfillment process by trucks. The main stakeholders are the dispatchers, the planners [18], and the designers of I-THINK-based simulators.

Spatial distribution of sectors based on the three scenarios already implemented: (a) Simulated, (b) Scheduled, and (c) Real, along with three data computation processes: (a) data reading/conditioning, (b) data processing, and (c) data writing to *Interface Human-Machine* (IHM) was established and assigned to quadrants. SIMUL V2© original spatial distribution is shown in Figure 4.2. Functions are implemented by the different structures of Stocks (Accumulators or Registers) and Flows (Entering-Leaving data enablers). SIMUL V2© design logic is based on years of experience in the concrete order fulfillment process. In order to describe the design logic and structures of every function, a spatial redistribution is carried out and the result is shown in Figure 4.3. Then every Quadrant is named by its corresponding matrix coordinate, as it shown in Figure 4.4. We proceed to describe each quadrant and its functionality.

Quadrant [1,1] Establish a simulation ("should be") loading minute based on verified conditions of execution and to generate synchronization signals for parallel processing on order information. The corresponding diagram is presented in Figure 4.5. Also, synchronize the truck transit time of each plant's services with the information of loading minute and volume through the simulation time. The corresponding diagram is presented in Figure 4.6.

Quadrant[2,1] Synchronize the cubic meter values of each service to its loading and transit times. The corresponding diagram is presented in Figure 4.7. Also, synchronize the scheduled loading minute with the actual loading time. The corresponding diagram is presented in Figure 4.8.

Quadrant [3,1] Establish the theoretical-one loading minute that is based on none consideration of execution conditions, and to count the number of services

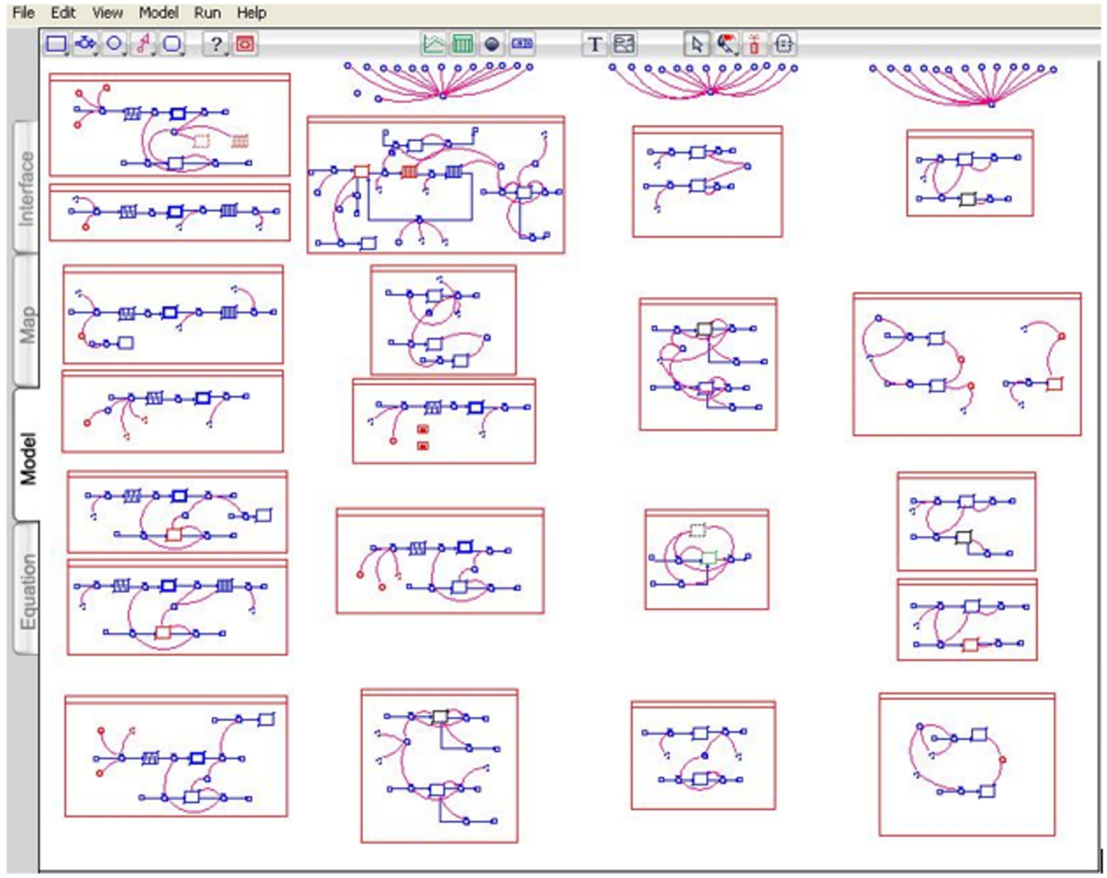


Figure 4.2: Current spatial distribution.

scheduled from the transactional database in a day. Execution conditions of free loading area and truck availability are ignored. The corresponding diagram is presented in Figure 4.9. Also, establish the theoretical-two loading minute that is based on the free loading area condition. The condition of truck availability is ignored. The corresponding diagram is presented in Figure 4.10.

QUADRANT [4,1] Synchronize the actual loading minute with the simulation time, and to count the number of services fulfilled in a day. The corresponding diagram is presented in Figure 4.11.

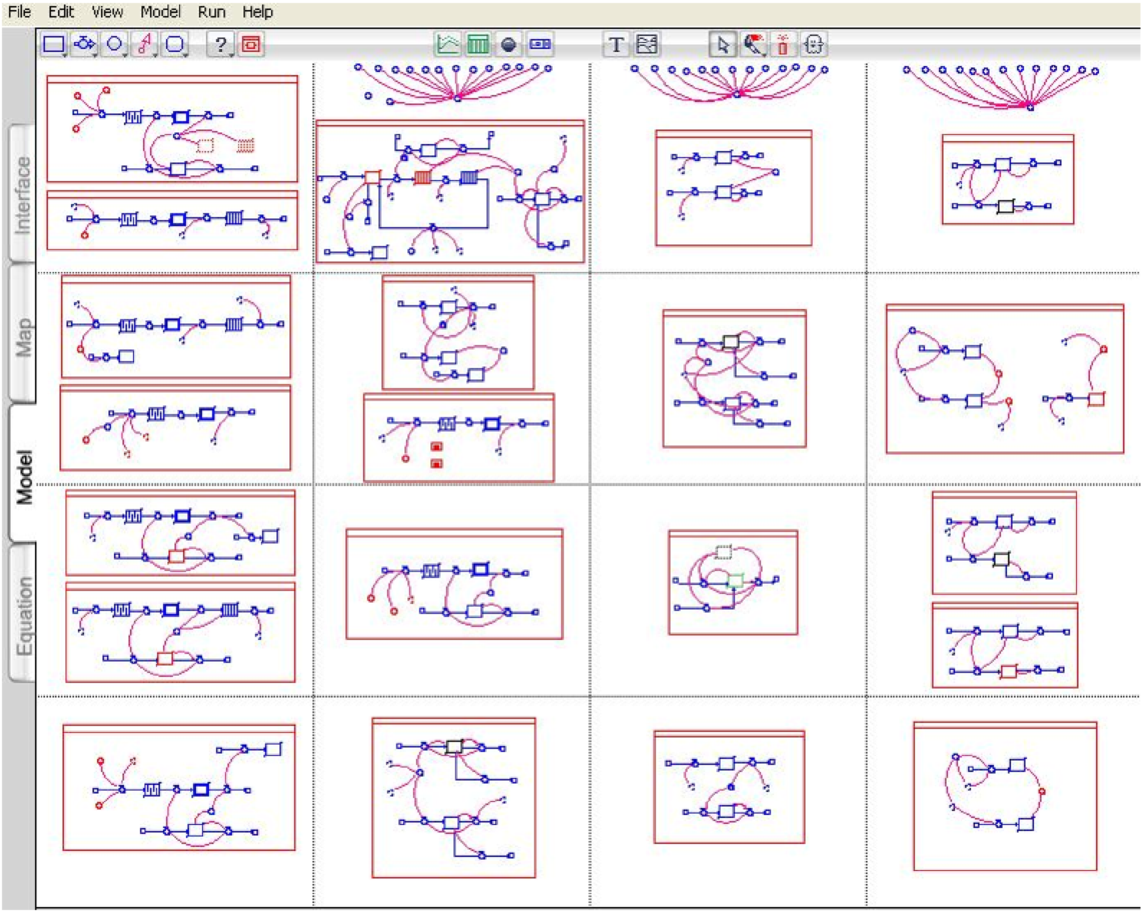


Figure 4.3: Current spatial distribution on Figure 4.2 to be referred by quadrants.

Quadrant [1,2] Estimate the following indicators for truck allocation performance by simulation: minutes of trucks' stay at plant, minutes without trucks in each plant, and required trucks per hour. The corresponding diagram is presented in Figure 4.12.

Quadrant [2,2] Compute the average cycle time at each plant by simulation. The corresponding diagram is presented in Figure 4.13. Also, index each service by simulation according to a input file. The corresponding diagram is presented in Figure 4.14.

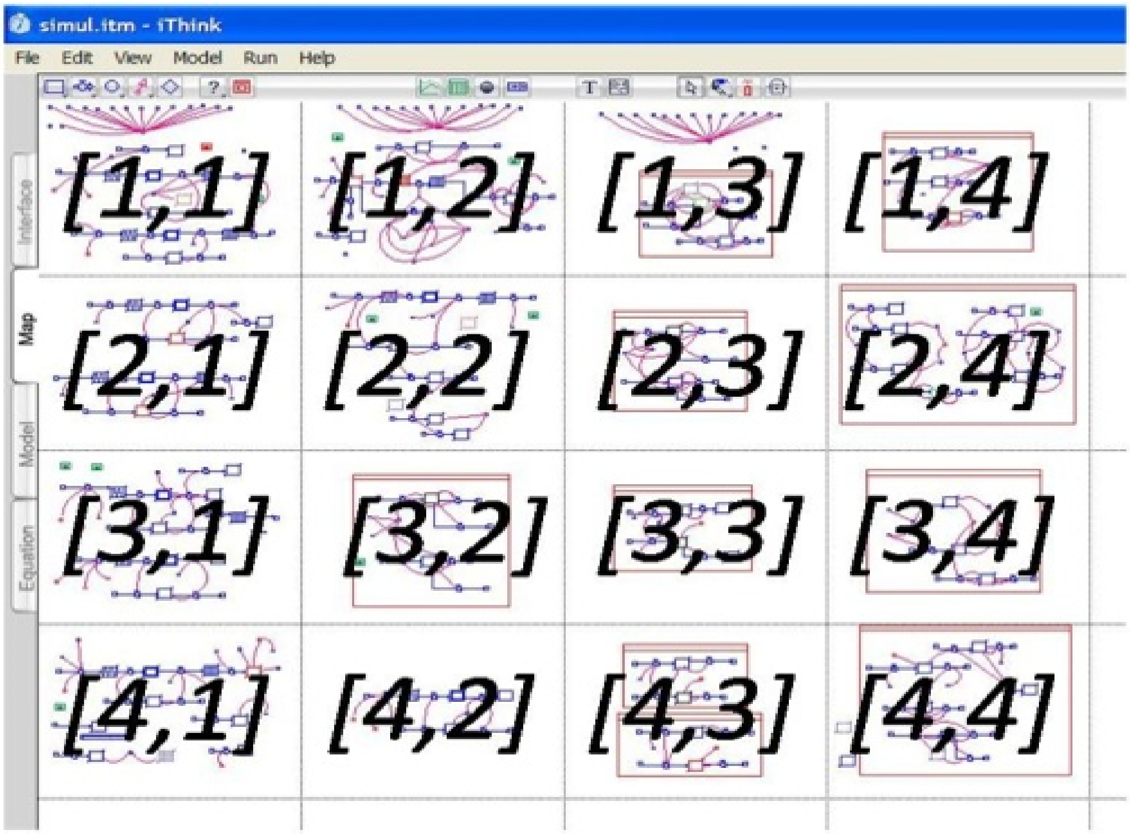


Figure 4.4: Spatial distribution organized by quadrants.

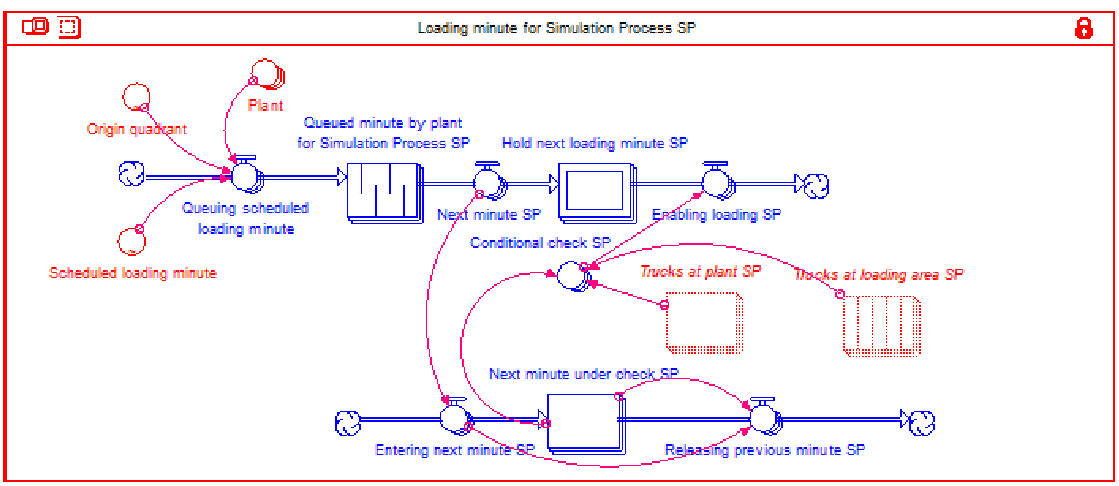


Figure 4.5: Loading minute for Simulation Process.

QUADRANT [3,2] Establish the actual truck arrival time. The corresponding diagram is presented in Figure 4.15.

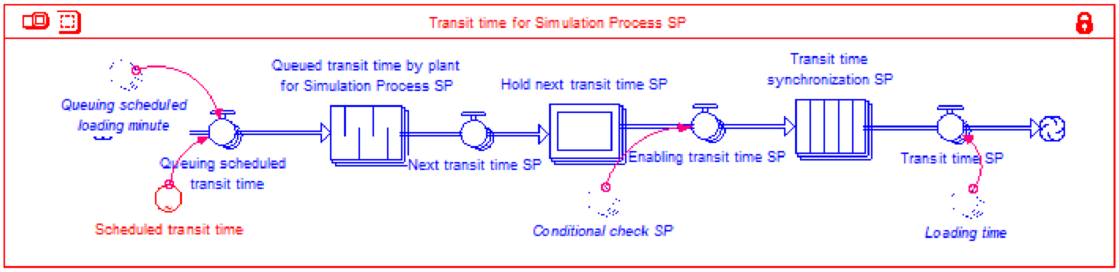


Figure 4.6: Transit time for Simulation Process.

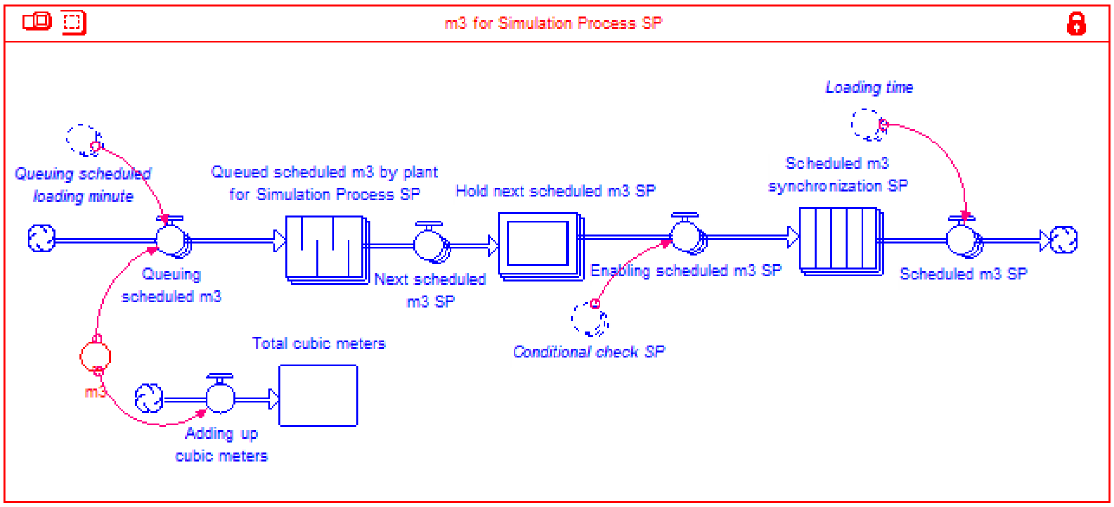


Figure 4.7: Cubic meters (m^3) for Simulation Process.

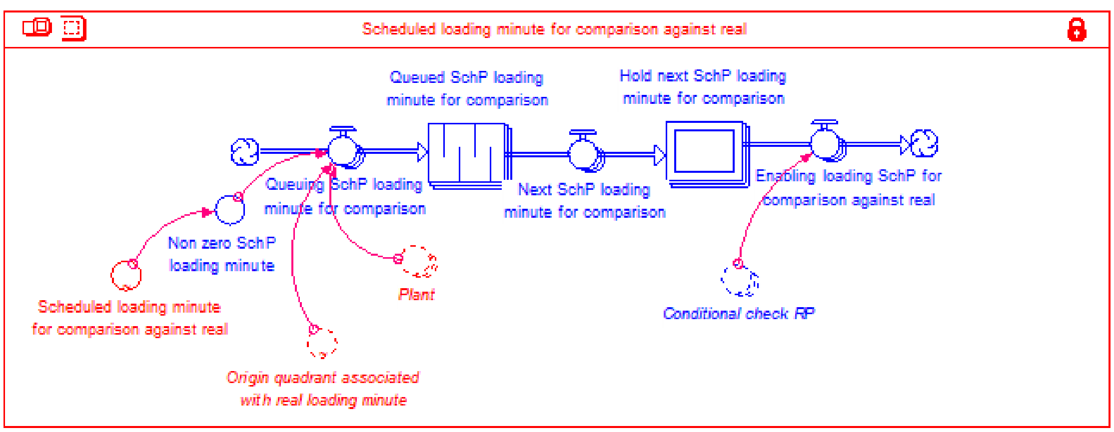


Figure 4.8: Scheduled loading minute for comparison against real.

Quadrant: [4,2] Register the delay in minutes between the actual loading time and the programmed loading time and establish the greatest delay hourly. The

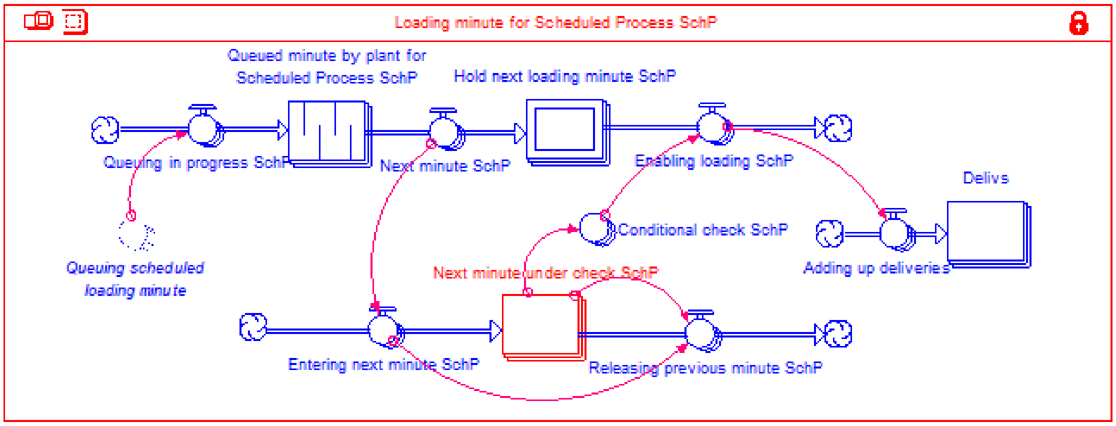


Figure 4.9: Loading minute for Scheduled Process.

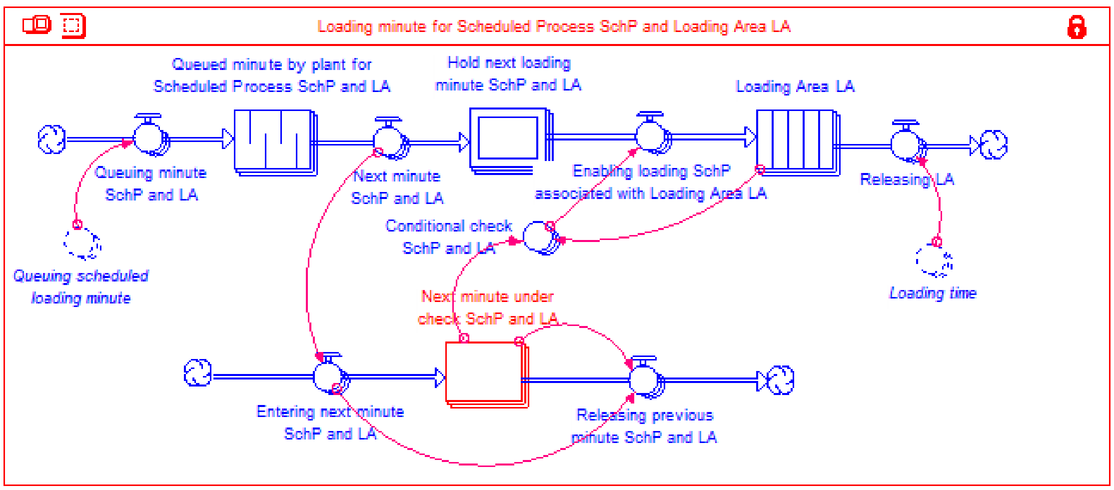


Figure 4.10: Loading minute for Scheduled Process and Loading Area.

corresponding diagram is presented in Figure 4.16.

QUADRANT [1,3] Establish the amount of services delayed per hour by simulation. The corresponding diagram is presented in Figure 4.17.

QUADRANT [2,3] Establish the greatest delay per hour per plant by simulation. The corresponding diagram is presented in Figure 4.18.

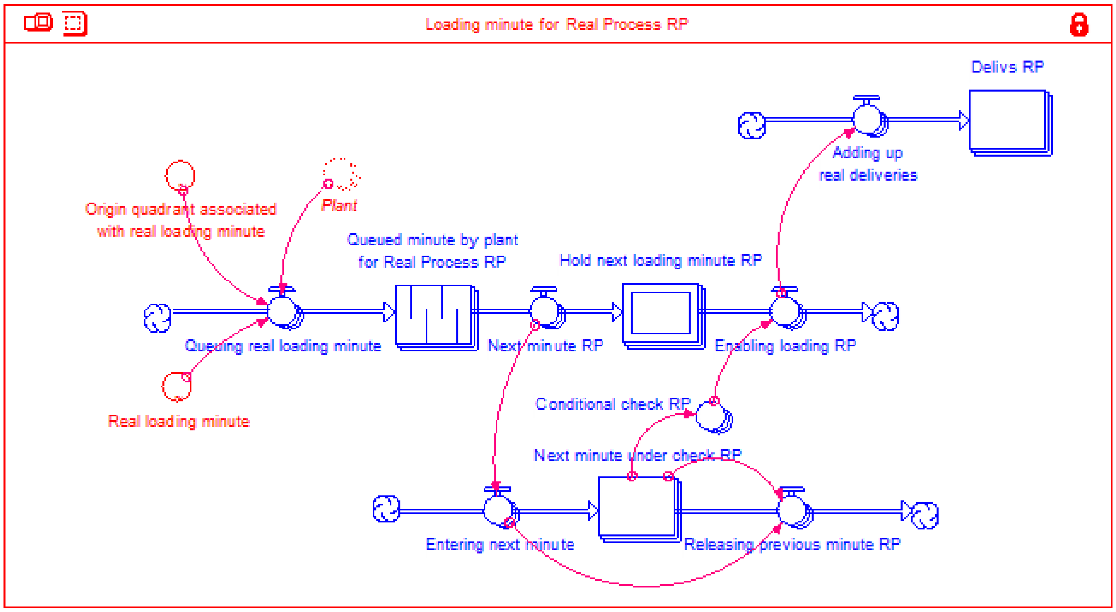


Figure 4.11: Loading minute for Real Process.

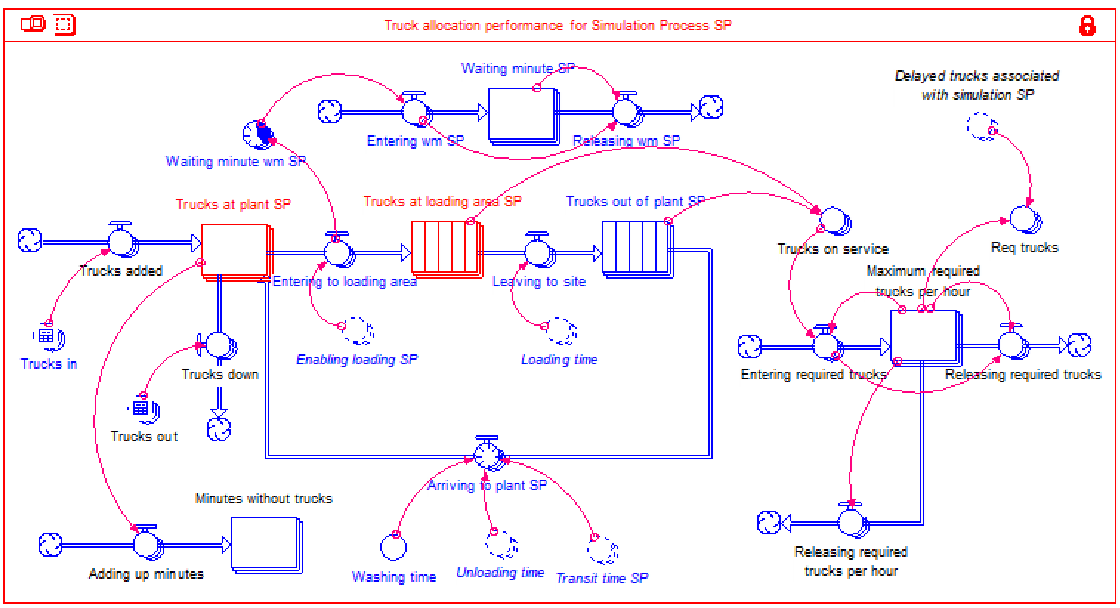


Figure 4.12: Truck allocation performance for Simulation Process.

Quadrant [3,3] Register the minimum amount of trucks available per plant in the course of each hour by simulation.

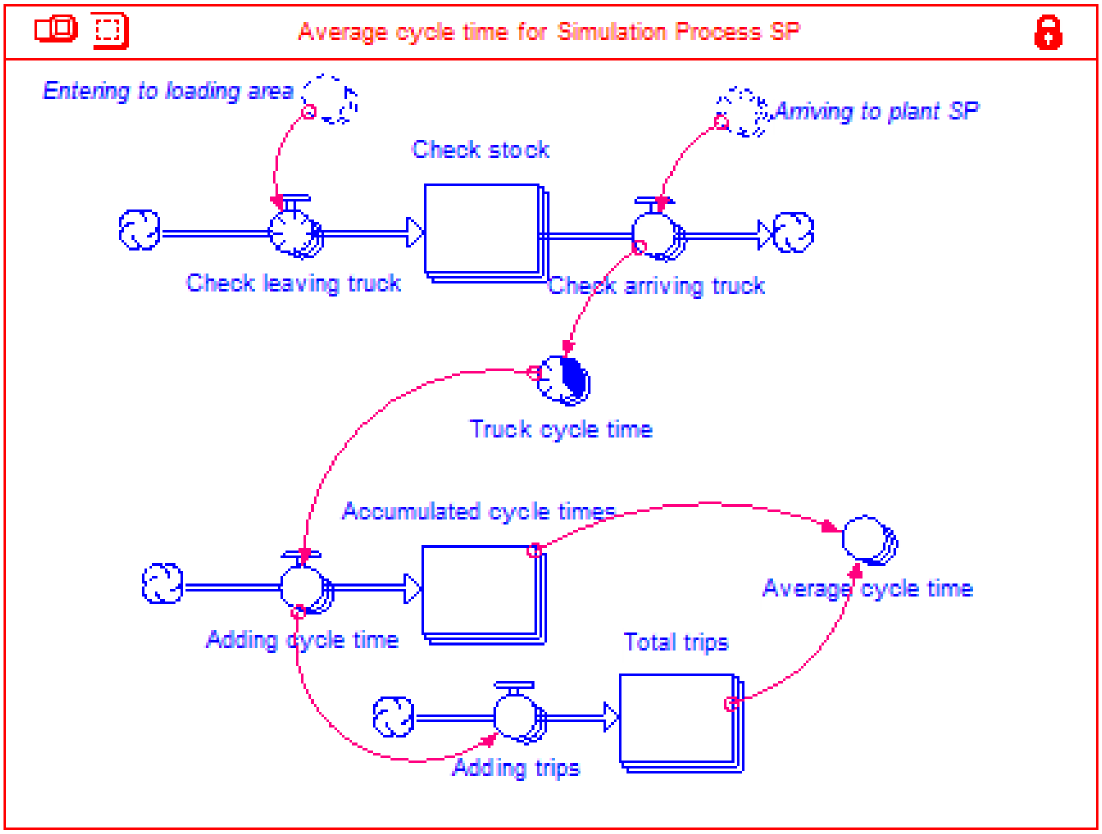


Figure 4.13: Average cycle time for Simulation Process.

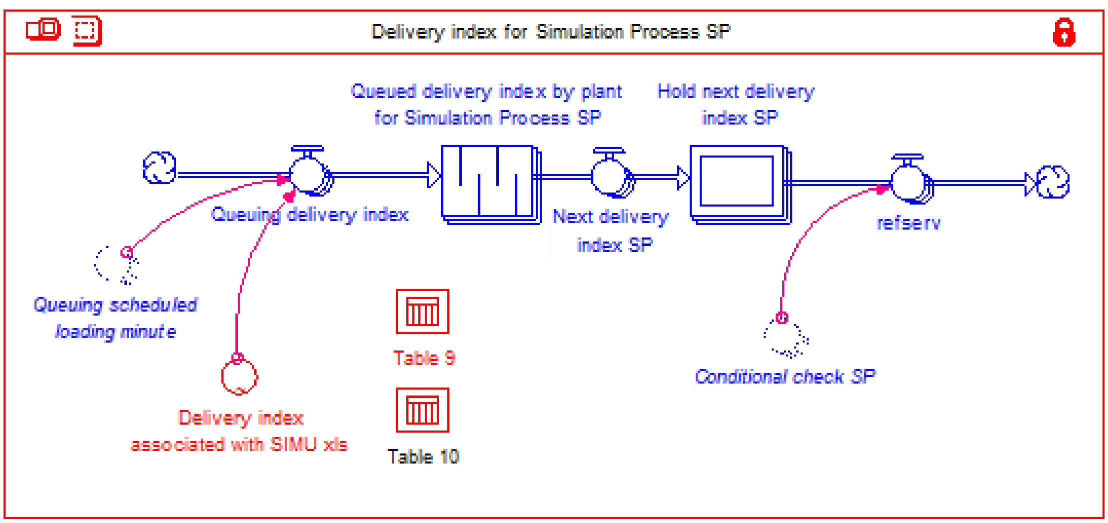


Figure 4.14: Delivery index for Simulation Process.

QUADRANT [4,3] Estimate trucks actual stay at plant, the minimum number of trucks required in each plant, and minutes of plant without trucks. The correspond-

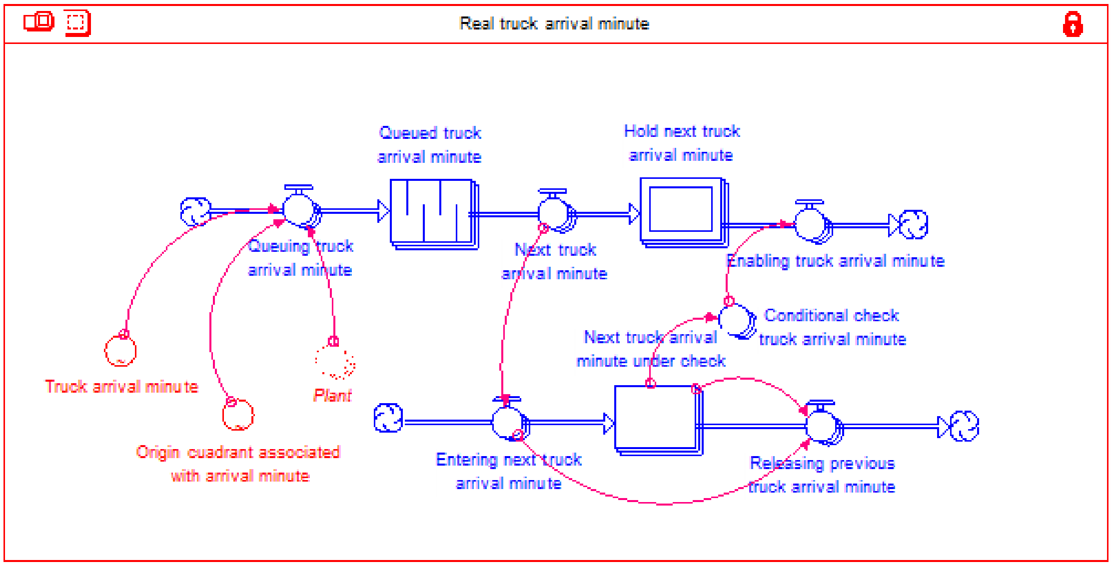


Figure 4.15: Real truck arrival minute.

ing diagram is presented in Figure 4.20.

QUADRANT [1,4] Count and register the amount of services per hour by simulation. The corresponding diagram is presented in Figure 4.21.

QUADRANT [2,4] Calculate the percentage of scheduled services loaded on time, trips per truck, m^3 per truck, and total m3 produced by plant under the simulation process. The corresponding diagram is presented in Figure 4.22.

QUADRANT [3,4] Establish the total programmed *theoretical* amount of services demanded per hour. The corresponding diagram is presented in Figure 4.23. Also, establish the amount of actual loaded services per hour. The corresponding diagram is presented in Figure 4.24.

QUADRANT [4,4] Calculate the percentage of actual services loaded on time. The corresponding diagram is presented in Figure 4.25.

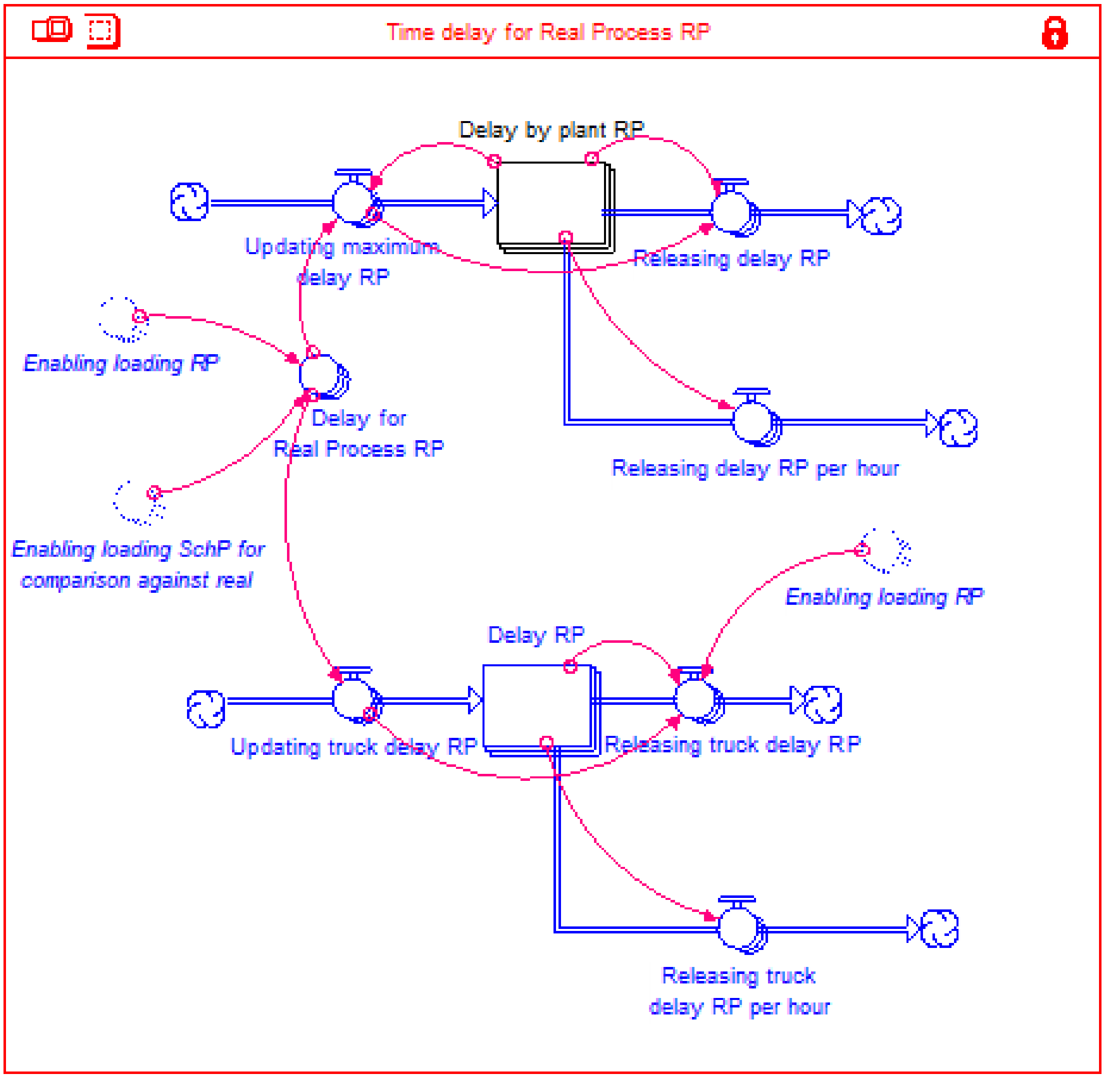


Figure 4.16: Time delay for Real Process.

4.3 Monitoring Tool

This section describe the integration of the dynamic model into a decision support system that permits to monitor the dynamics of the problem. The monitoring tool has been developed using JavaScript, HTML5, and mapExperience plus. Clustering and centroid algorithms are incorporated to observe customer demand by volume, quantity of orders; and a minimum cost algorithm to know the number of

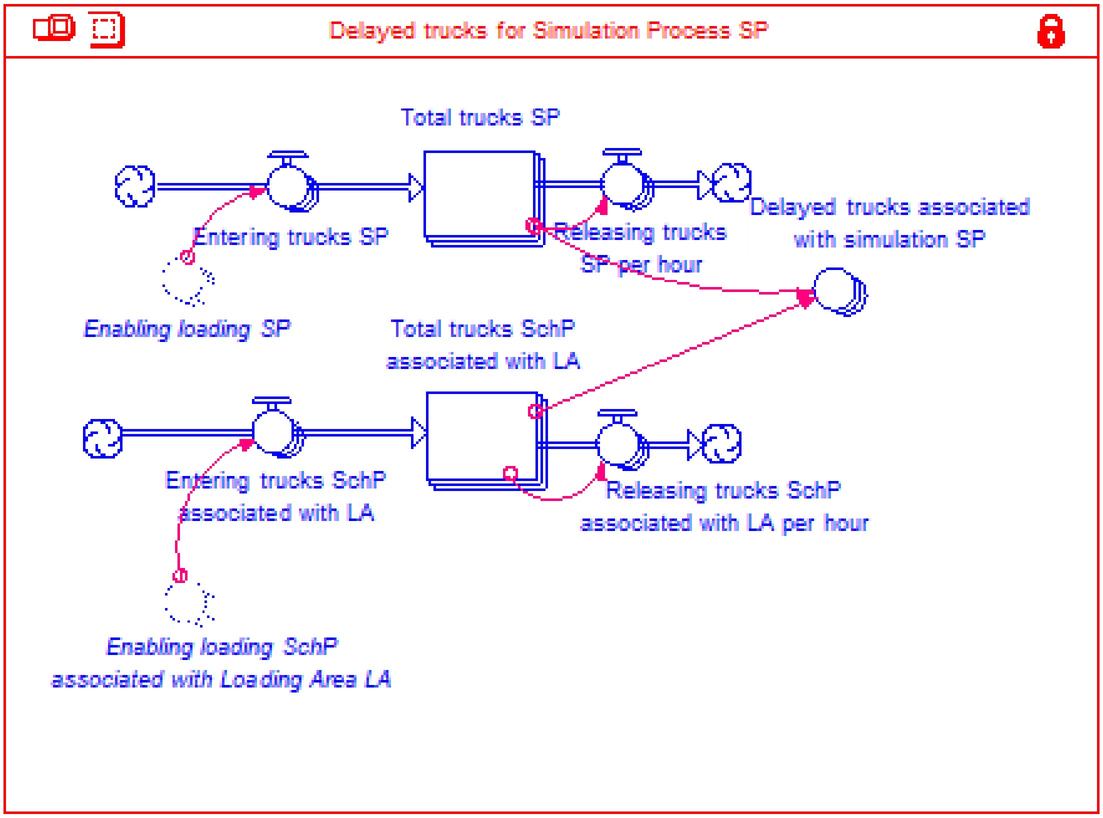


Figure 4.17: Delayed trucks for Simulation Process.

trucks that can be assigned.

The tool can be use to known the status of the trucks (stay in plant, towards the client, available, or idle time), as well as the status of an order (cancellation, start later or change frequency). As a visual aid, a color code is chosen to easily known the status of the truck, green: on the way to work, blue: on the floor with less than forty minutes, and red: standing for more than forty minutes inside a plant. With this color code it is easy to detect if the truck is in plant or if it has a longer cycle time than usual. To locate each truck, a GPS is installed (it can have errors of up to 200 meters) to obtain the speed.

The visualization allows to know the lack and the excess of trucks using the distance and the time of the origin plants. Our hypothesis is that an adequate

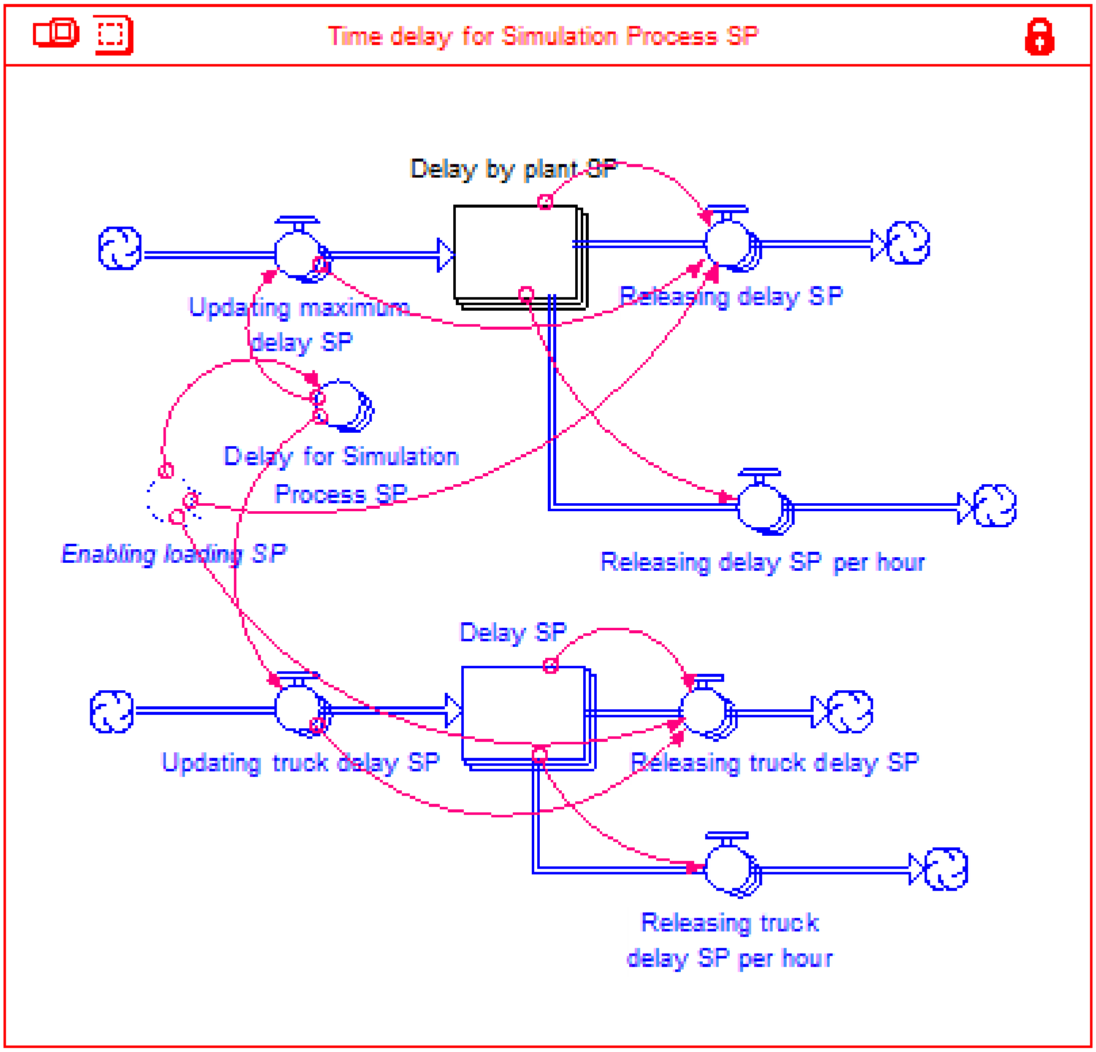


Figure 4.18: Time delay for Simulation Process.

allocation of the trucks is perform badly to support some client, the truck will be late with the client causing the dissatisfaction of the client. As an example, if the original plan was to arrive at 3:00 p.m. with the client, by not making an adequate allocation of the trucks and by delays of the plant where he must serve ends up arriving an hour later at 4:00 p.m. To perform the clustering, the assumptions made are based on the distance and time of the plants, in addition, the Google API is used to obtain the amount of time on the journey to reach a customer.

The tool serves as visual support to the decision maker (for this particular

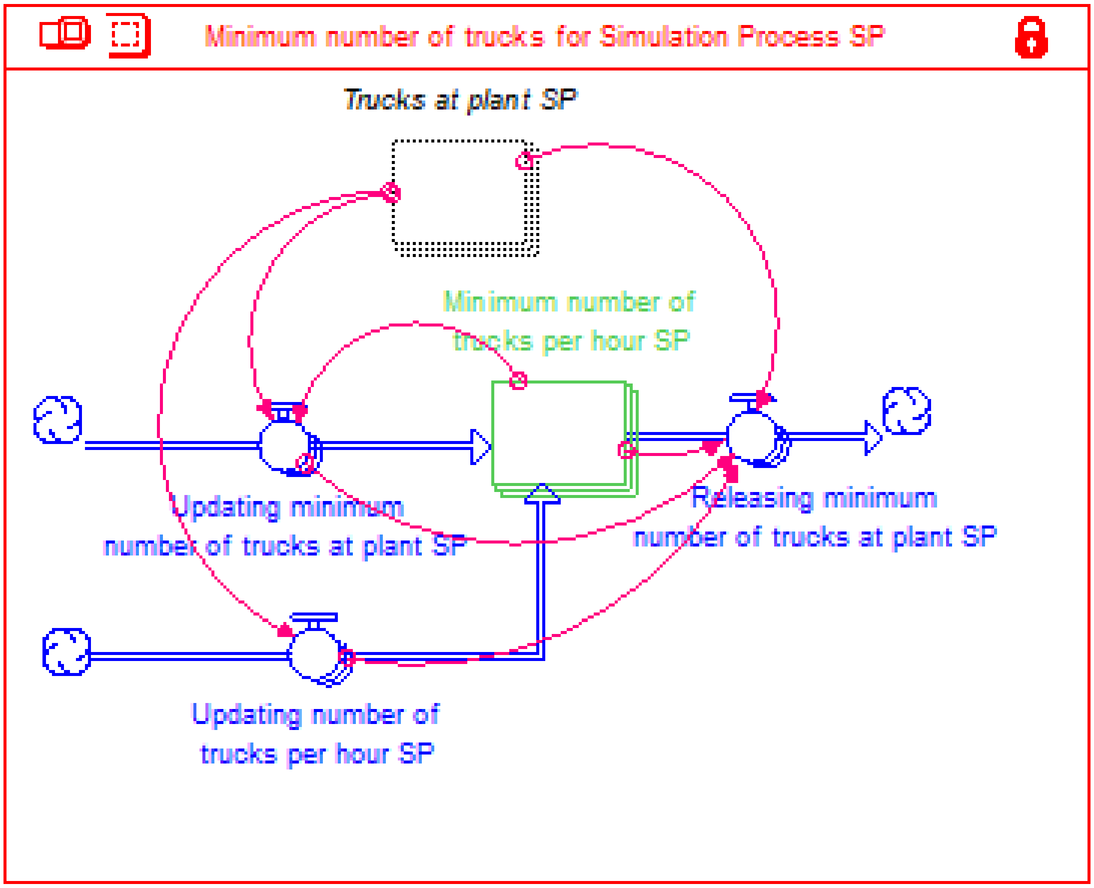


Figure 4.19: Minimum number of trucks for Simulation Process.

case would be the dispatchers, responsible for the allocation of trucks to orders) and allows the user to distinguish in which places are available trucks and in what places trucks are needed to attend in time and form to as many customers as possible during the day. By having a broad overview of what happens on a day-to-day basis, you can have a better management of the operation as well as the number of trucks that are missing and also allows you to know the number of operators required on a particular day.

To visualize the demand of the clients by volume or services in a round, a centroid algorithm is used that allows grouping according to the ranges of the quantity to be visualized. With this it is possible to detect which plant has greater impor-

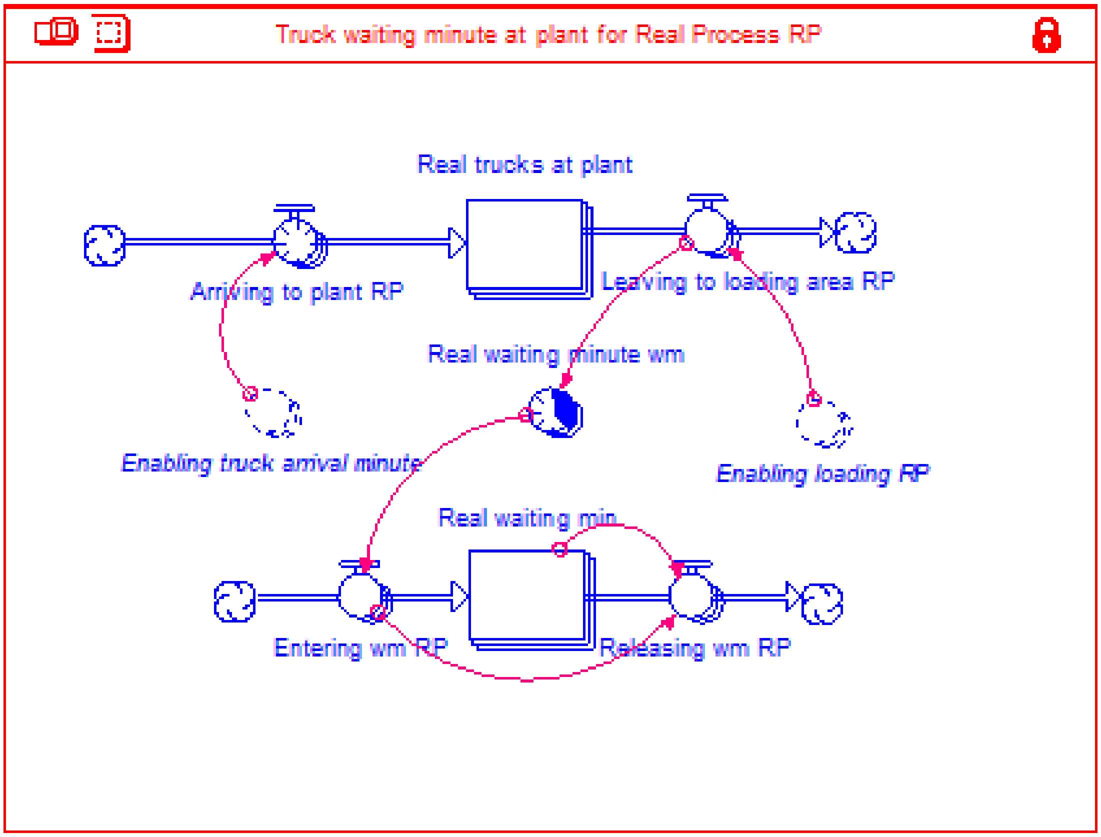


Figure 4.20: Truck waiting minute at plant for Real Process.

tance, that is, the plant whose region has the highest concentration of demand. We know how many trucks are present so as not to pile up trucks and be able to make a decision instead of sending more units to the work. You know how many trucks are on the job.

Our interest is to cover the customer demand, keeping that in mind the tool can concentrate the areas where idle trucks exists in order to help the dispatcher in which number of trucks are available to cover that areas where other customers may not be served due to the lack of trucks. The core of the algorithm is based on the time cycle between plants and customers and allows to know the number of trucks, per round, that the company need to support the areas where customers may not be serve. An example of the required trucks for four job sites and two plant is presented

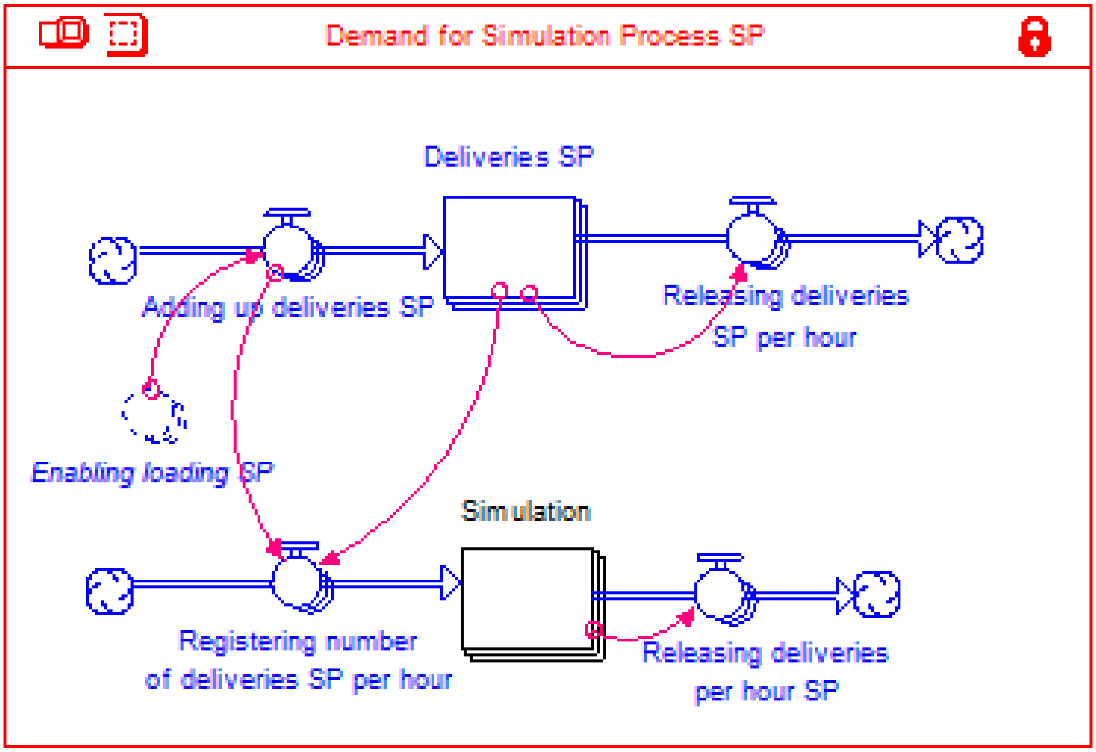


Figure 4.21: Demand for Simulation Process.

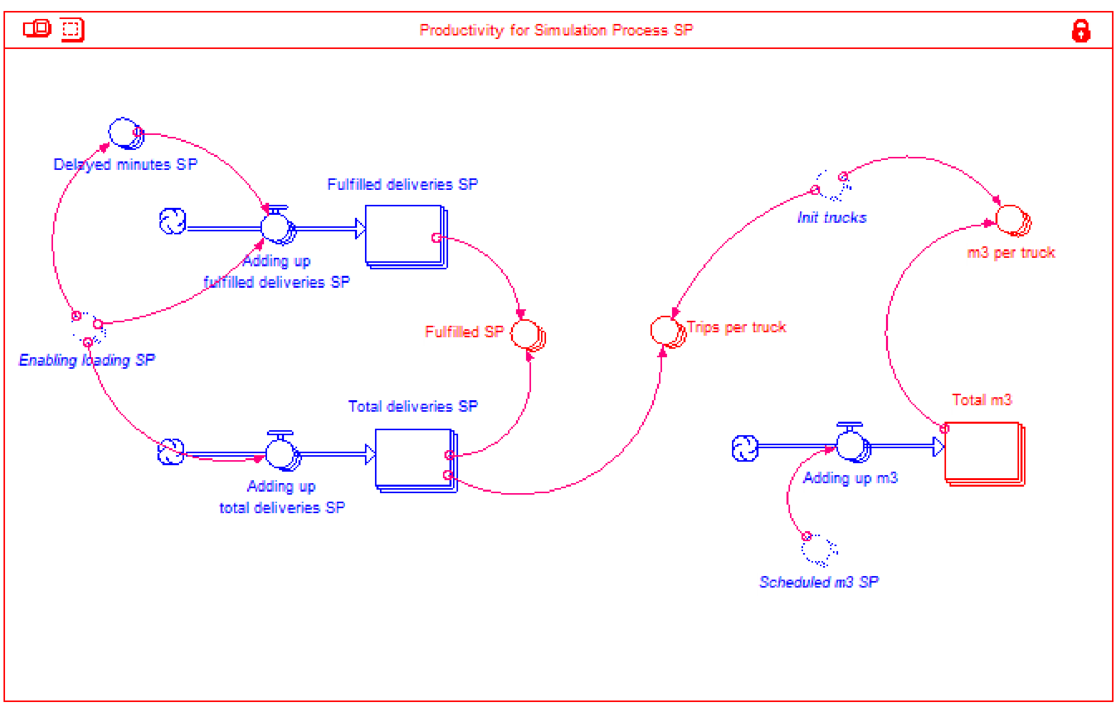


Figure 4.22: Productivity for Simulation Process.

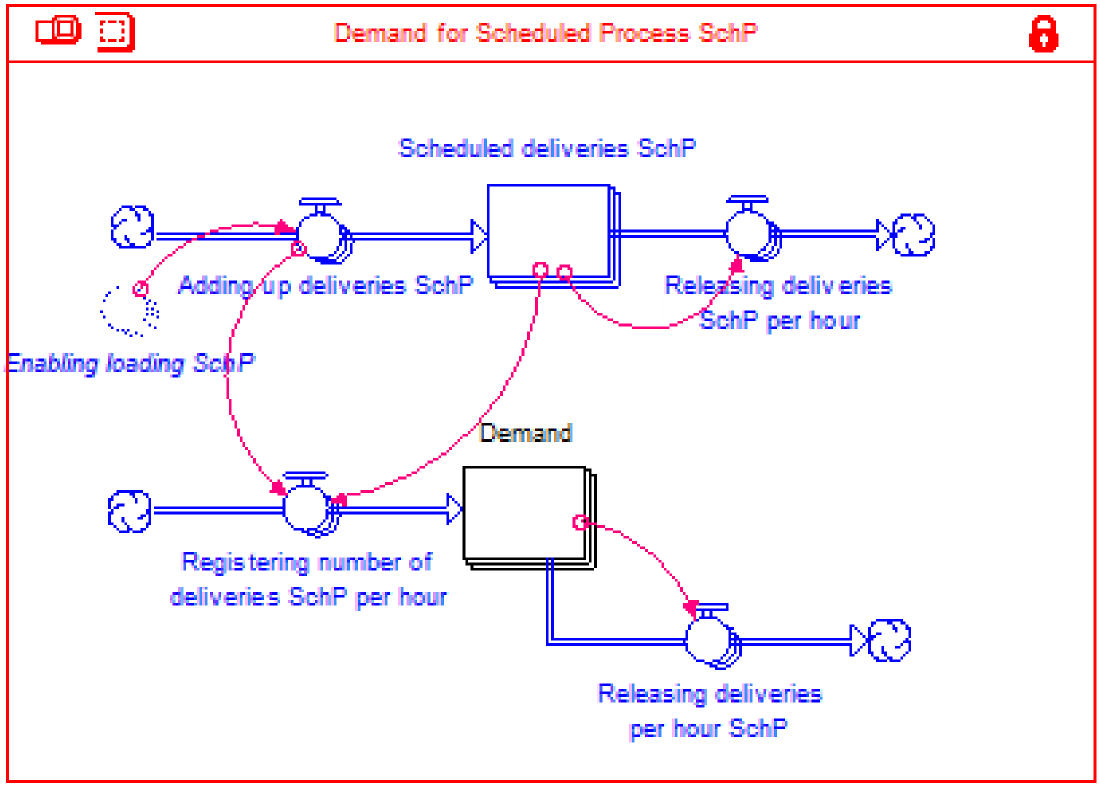


Figure 4.23: Demand for Scheduled Process.

in Figure 4.26.

Also, the algorithm consider the percentage of usage of each plant, an estimate of customers serve in the round and which will be attended in next rounds, and the delivery times in the day in order to minimize surpluses and deficits. It is based on the centroid, to distribute truck demand, customer demand translated into the trucks they need. Naturally, the demand is greater than the one that can be met, but since there is a possibility that a customer cancels, or moving the order to another time, it is considered within the scope of attention. An example of how it is visualized to the dispatches is shown in Figure 4.27.

A sequence of illustrative examples is considered to show the benefits of the dynamic model. In the first example (see Figure 4.28 to 4.31), there are two customers with one service each one, Jobsite 1 and Jobsite 2, respectively. The resources of the

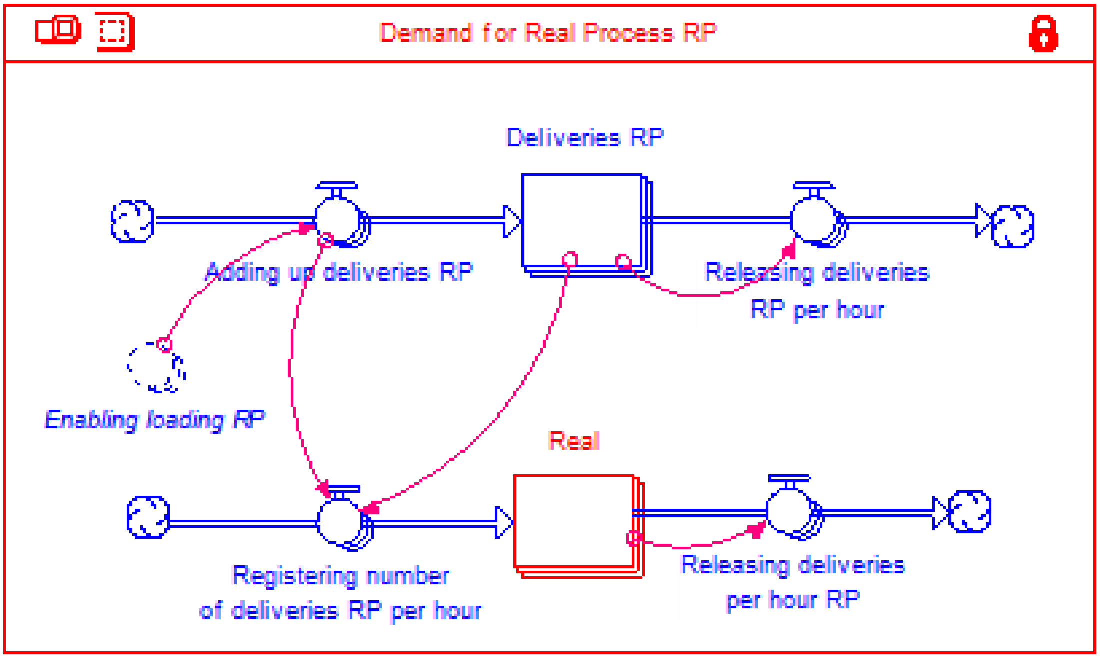


Figure 4.24: Demand for Real Process.

company are two plants, Plant 1 and Plant 2. There is one slot available on Plant 1 and eight slots in Plant 2 (see Figure 4.28). The traveling time from Plant 1 to Jobsite 1 is 15 min and from Plant 2 to Jobsite 1 is 25 min. The traveling time from Plant 1 to Jobsite 2 is 5 min and from Plant 2 to Jobsite 1 is 30 min. The Jobsite 1 make the first call, he request a service and the service agent assign the Plant 1 to serve him as is the closest plant to Jobsite 1, this removes the available slots on Plant 1 (see Figure 4.29). Later, Jobsite 2 call for a service (see Figure 4.30). The closest plant is Plant 1 but as there is no slots available, the Plant 2 is assignment to serve her (see Figure 4.31). The total traveling time is 45 min.

Now consider another example (see Figures from 4.32 to 4.35), there are two customers, one with two services and the other with ten services, Jobsite 3 and Jobsite 4, respectively. The resources of the company are two plants, Plant 3 and Plant 4. There is ten slots available on each plant (see Figure 4.32). The traveling time from Plant 3 to Jobsite 3 is 5 min and from Plant 4 is 15 min. The traveling

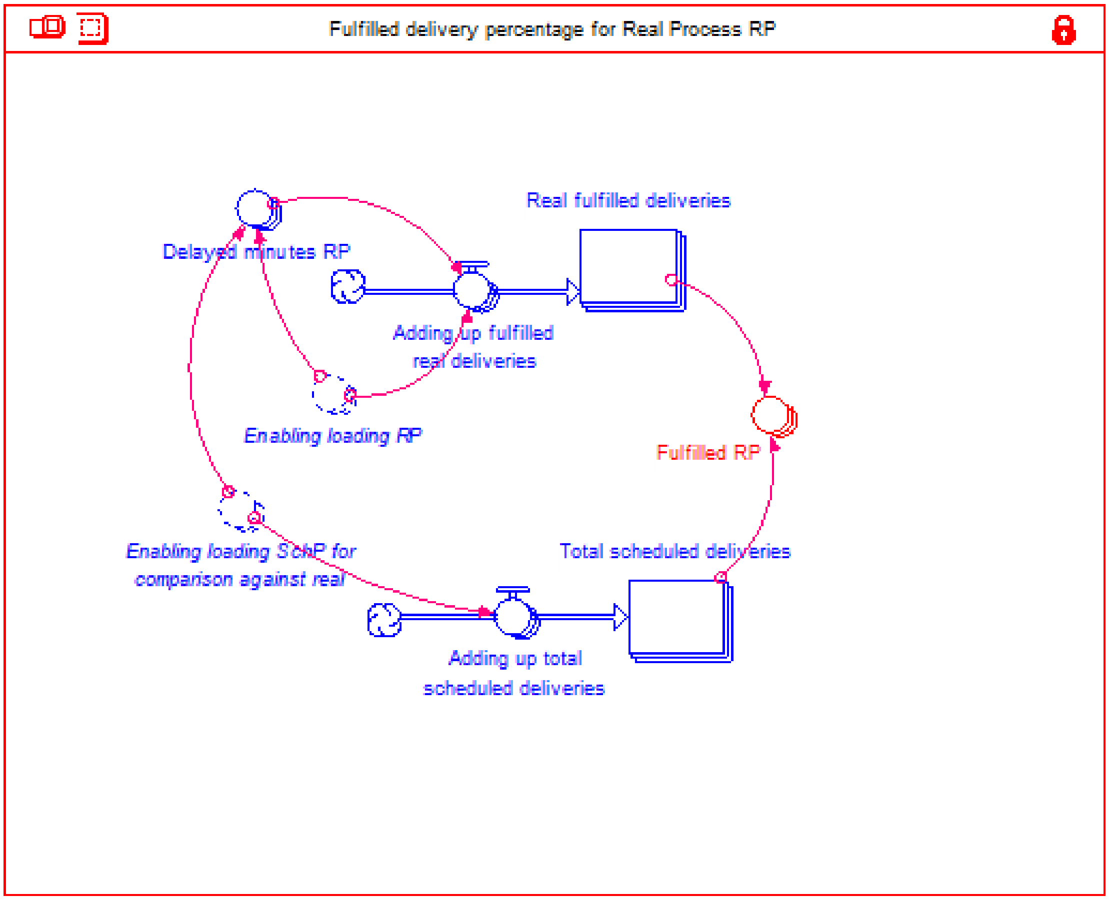


Figure 4.25: Fulfilled delivery percentage for Real Process.

time from Plant 3 to Jobsite 4 is 7 min and from Plant 2 is 20 min. The Jobsite 3 make the first call, he request two service and Plant 3 is assigned to him as is the closest plant to Jobsite 3, leaving it to eight available slots (see Figure 4.33). Later, Jobsite 4 call for for a delivery of ten services (see Figure 4.34). The closest plant is Plant 3 but she needs ten slots available and Plan 3 only have eight slots, therefore, the Plant 4 is assignment to serve her (see Figure 4.35). The total traveling time is 210 min.

In both examples, if we execute the dynamic model, the result is optimized to reallocate each serves to the closest plant. In the first example there is a decrease of 15 min from the initial assignment and in the second example there is a reduction of 100 min as shown in Figure 4.36.

Now, another example with more customers and more plants. The example is illustrated from Figure 4.37 to 4.40. In this example there are three plants and sixteen customers assigned (see Figure 4.37). The plants of the left have not available slots and the plant on the right have five slots available. If a new customer arrive close to those plants without available slots, as shown in Figure 4.38, the customer is assigned to the plant with available slots (see Figure 4.39). This assignment generates monetary losses as the travel time is bigger than expected. To solve this, the model is executed and reassign the new customer to the closest plant and one of the customer of this plant, considering the traveling time, is assigned to the plant with available slots (see Figure 4.40).

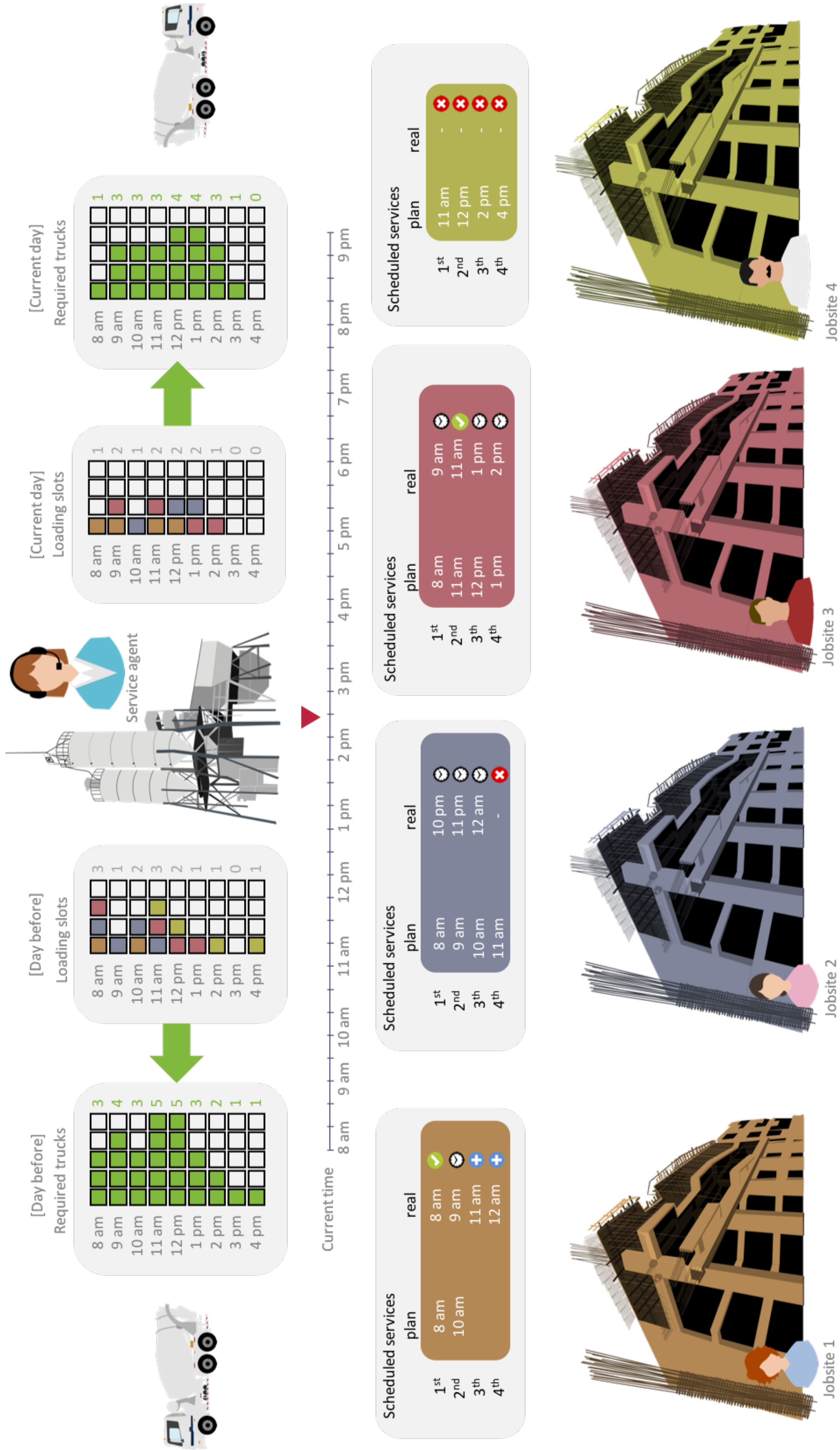


Figure 4.26: Example of required trucks considering the cycle time.

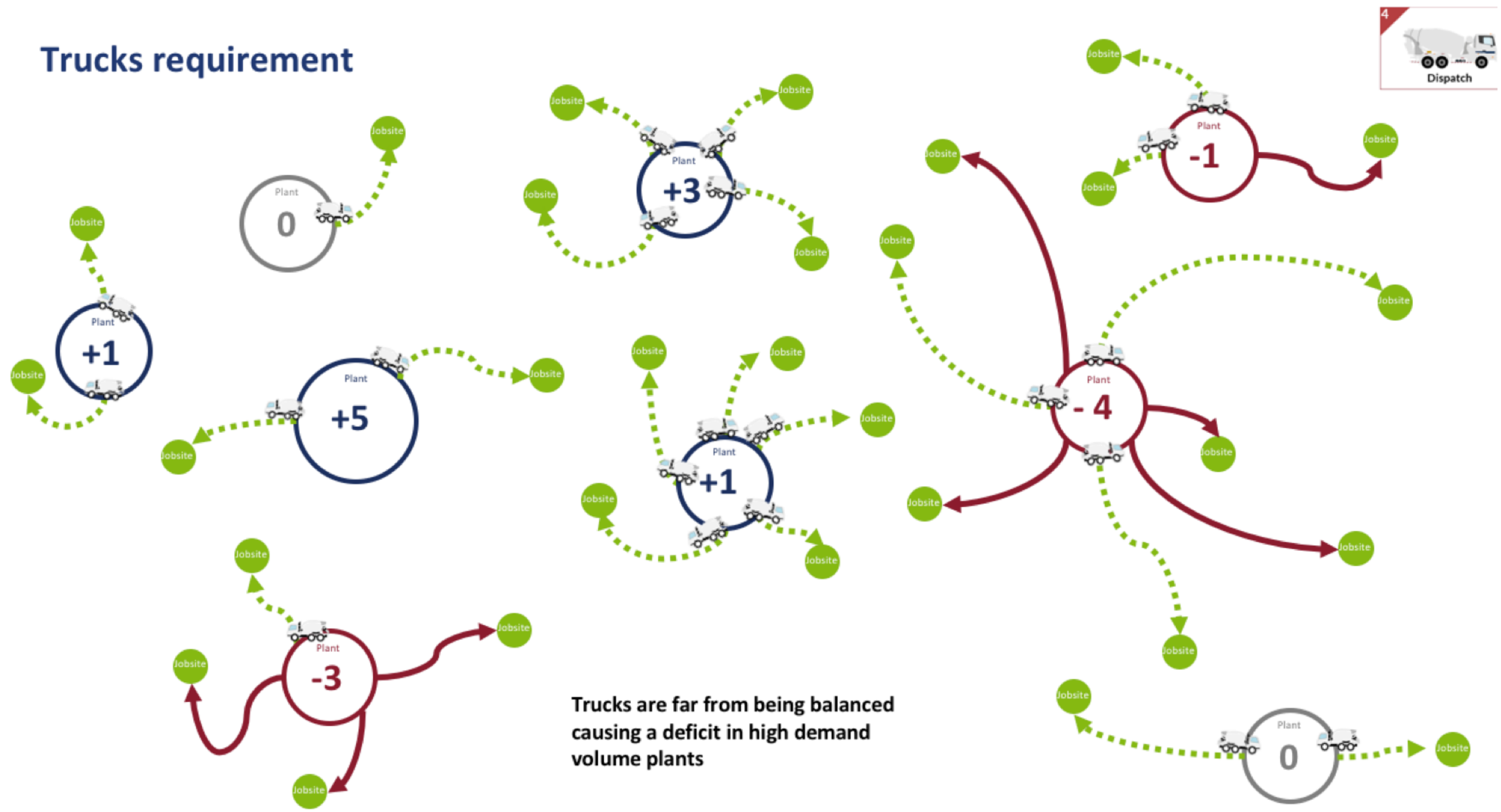


Figure 4.27: Truck balance for 9 plants (unfilled circles) to serve a total of 29 customers (green filled circles). The number inside each plant represent the number of surplus trucks (+), missing trucks (-), or not available trucks (0).

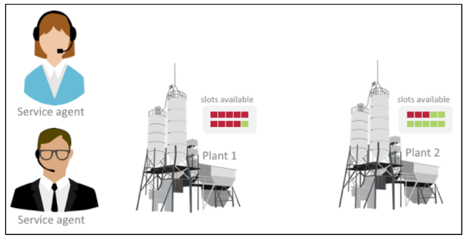


Figure 4.28: The illustration represent how the plants are occupied before an order arrives. Only two plants and two customers are considered.

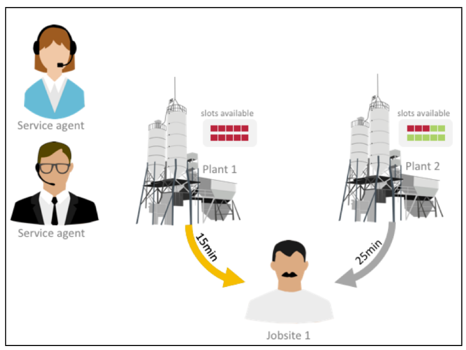


Figure 4.29: The illustration represent the moment after an order arrive. In this case the order of the Jobsite 1 is assigned to Plant 1, the closest plant.

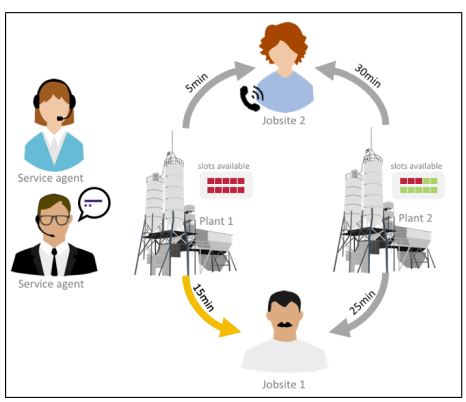


Figure 4.30: The illustration represent the moment after a second order arrive (Jobsite 2). The order is not assigned to any plant.

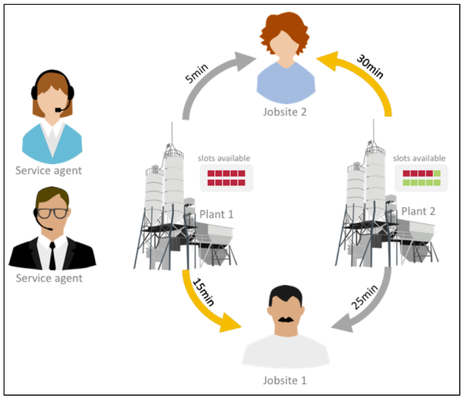


Figure 4.31: The illustration represent the moment after a second order arrive. The order of the Jobsite 2 is assigned to Plant 2.

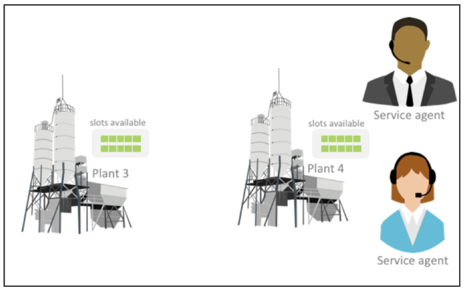


Figure 4.32: The illustration represent how the plants are occupied before an order arrives. Only two plants and two customers are considered. Both plants are with all its slots available.

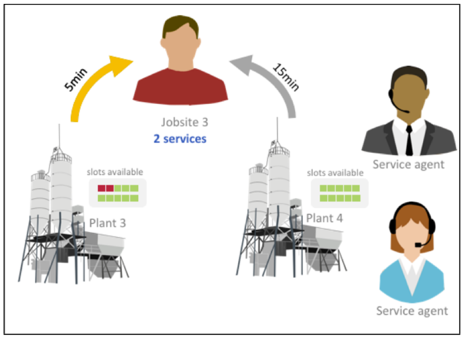


Figure 4.33: The illustration represent the moment after an order arrive. In this case, the two orders of the service from Jobsite 3 are assigned to Plant 3.

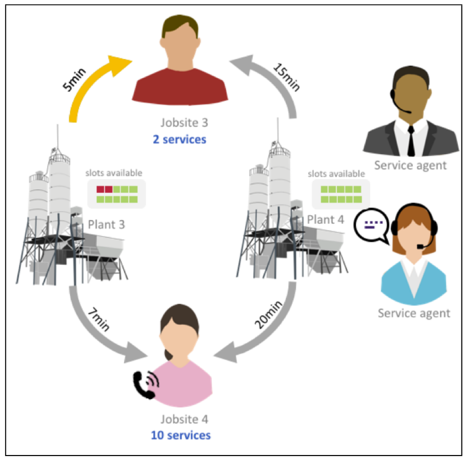


Figure 4.34: The illustration represent the moment after a second service arrive (Jobsite 4). The service with 10 services is not assigned to any plant.

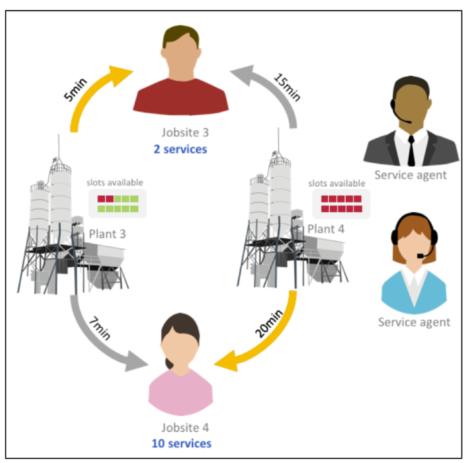


Figure 4.35: The illustration represent the moment after a second order arrive. The order with 10 service of the Jobsite 4 is assigned to Plant 4 as it is the plant with 10 available slots.

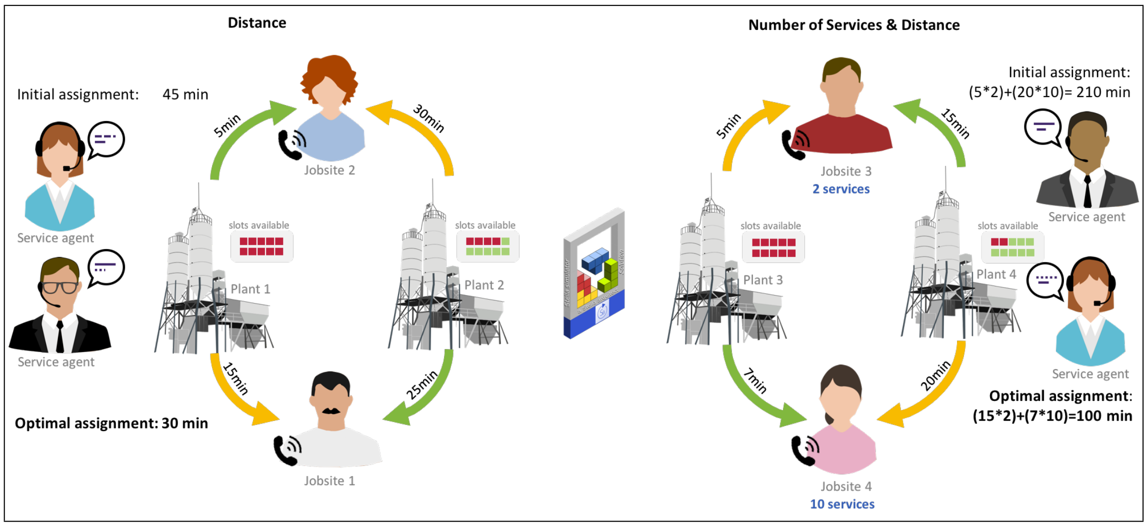


Figure 4.36: Illustration of the optimization performed by the engine. For each scenario, all orders are assigned to the closest plants yielding a reduction of the total traveled distance.

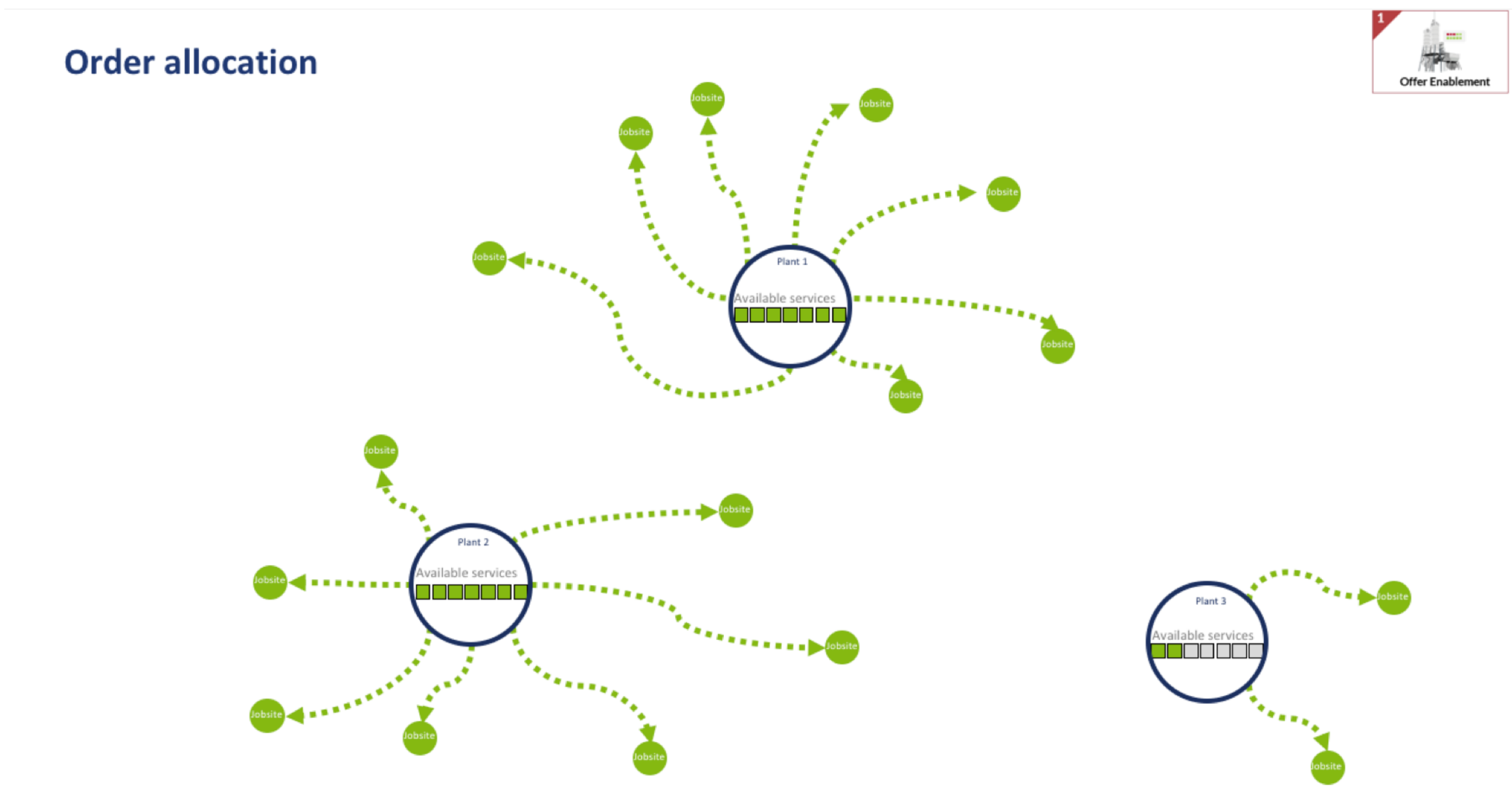


Figure 4.37: Illustration of an example before an new client arrives. The example considers 3 plants with 17 clients with its orders assigned. Only Plant 3 have available slots.

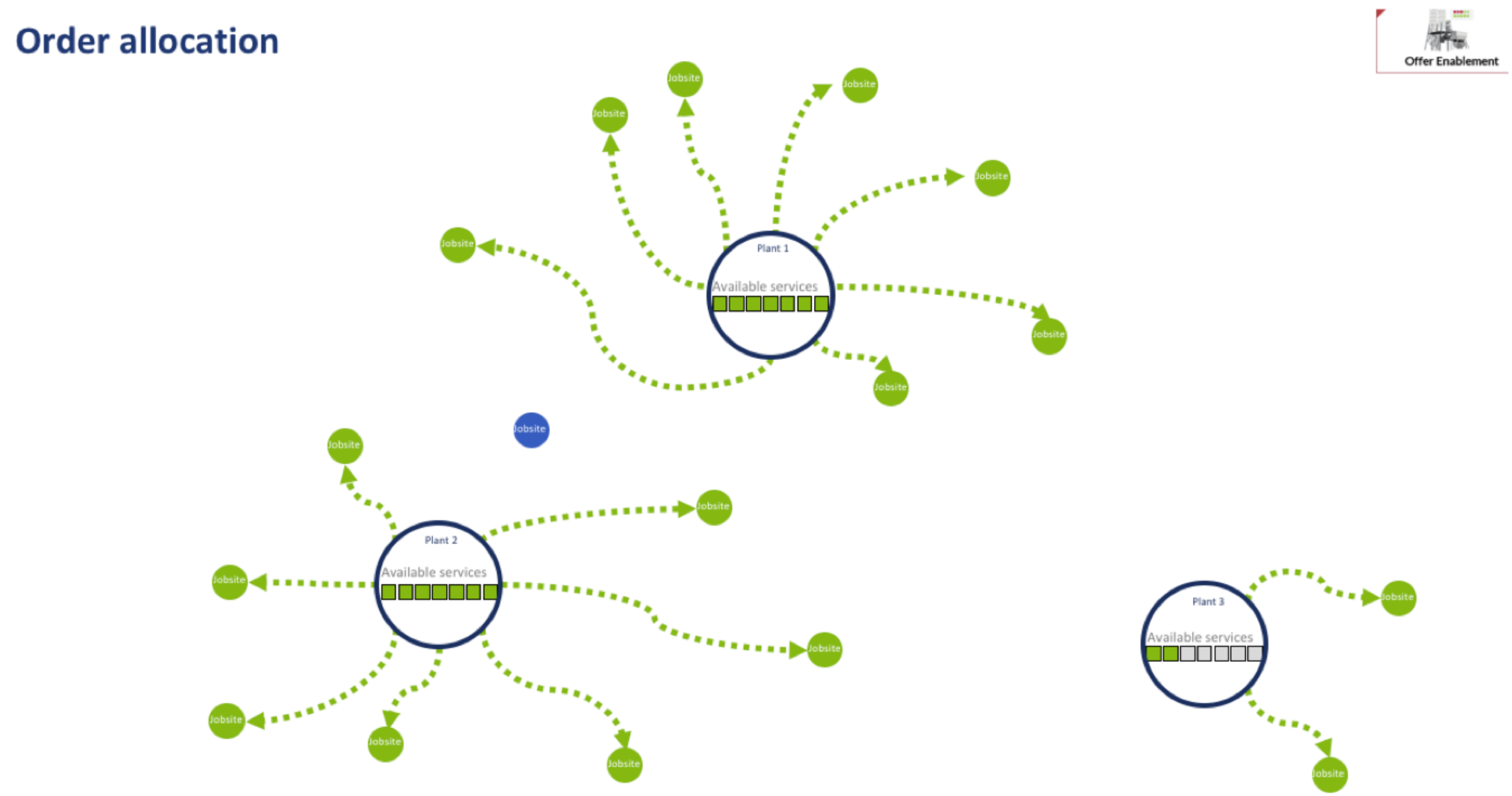


Figure 4.38: Illustration of the new customer arrival. The Plant 3 is the farest plant to the client. Plant 1 and Plant 2 are the closest.

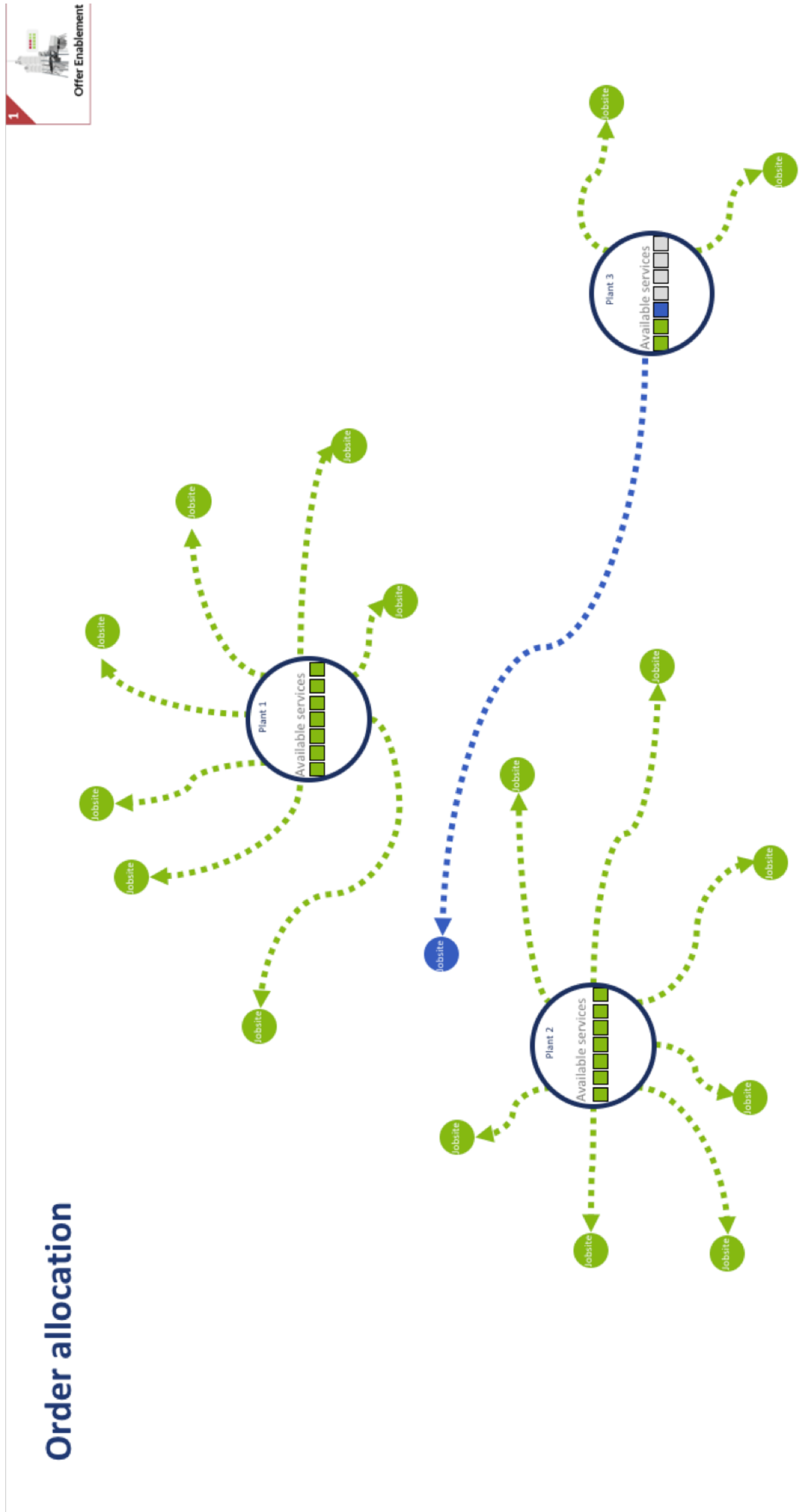


Figure 4.39: Illustration of the assignment of the new client to the farest plant, Plant 3.

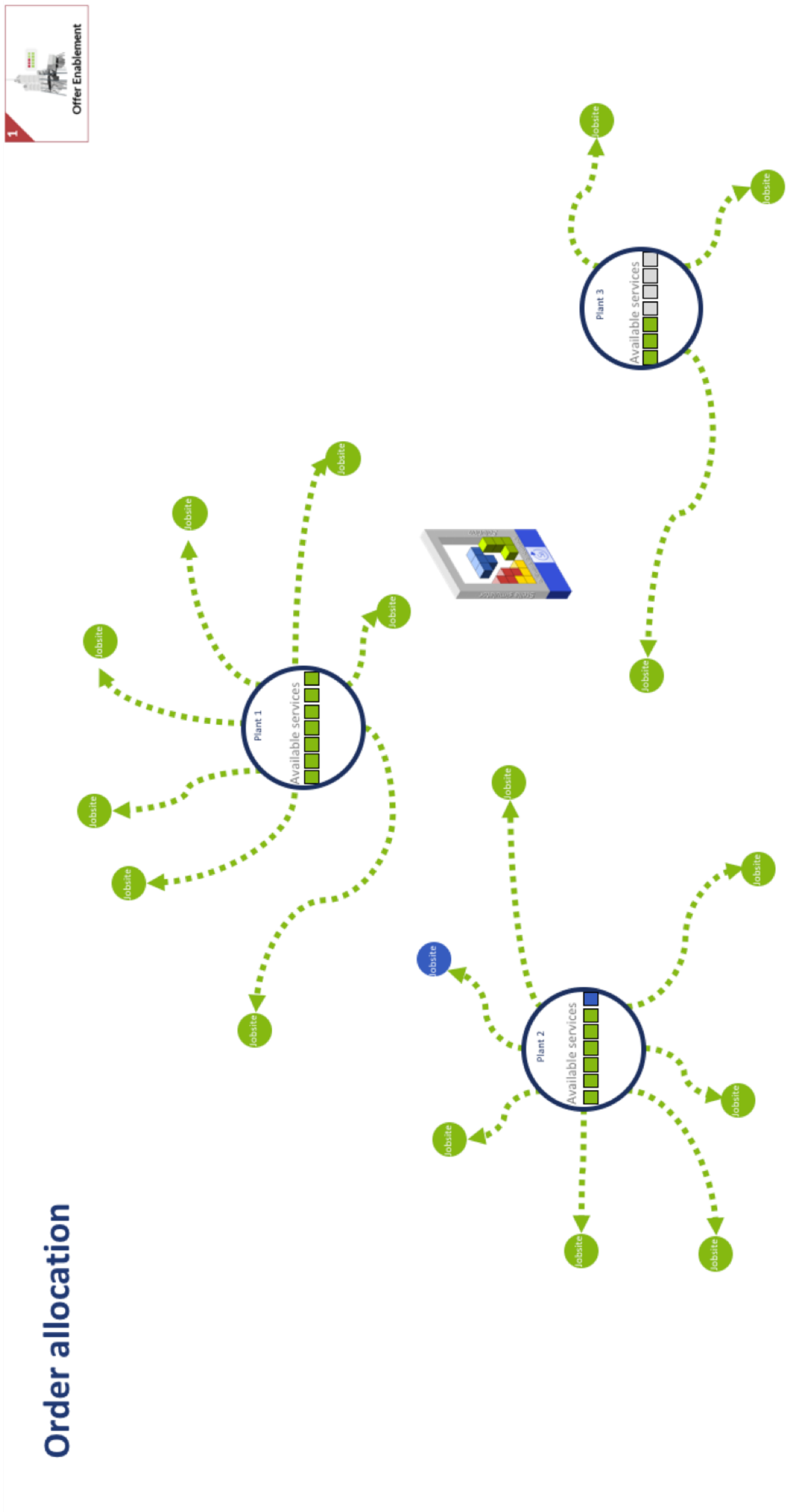


Figure 4.40: Illustration after the optimization performed by the engine. The new clients now is assigned to Plant 2 by dropping one service that is re-assigned to its closes plant, that is Plant 3.

Chapter 5

Computational Experiments

The company need fast methods to obtain good scenarios that can help the decision maker in every day dispaching and planning. Real-time responsiveness is more important than exact optimization in a less timely fashion. Therefore, a decision-support engine is proposed to help the decision maker in day-on-day operations. If desired, the decision maker may then utilize knowledge that is not known to the engine to improve the schedule. The engine can be set up as a loop where the decision maker works iteratively with the solver to generate an ever-improving solution. This chapter begins with a description of the characteristics and core tools of the proposed engine.Then a description of the case under study which include some components that are used to propose the solution using the decision-support engine with a dynamic system tool and a visualization tool.

5.1 Decision Support Engine

The main core of the engine is a system dynamic tool based on i Think application to support operational planning and optimization of resource allocation in the ready-mix concrete order fulfillment process. Up today, trucks are the specific resources to

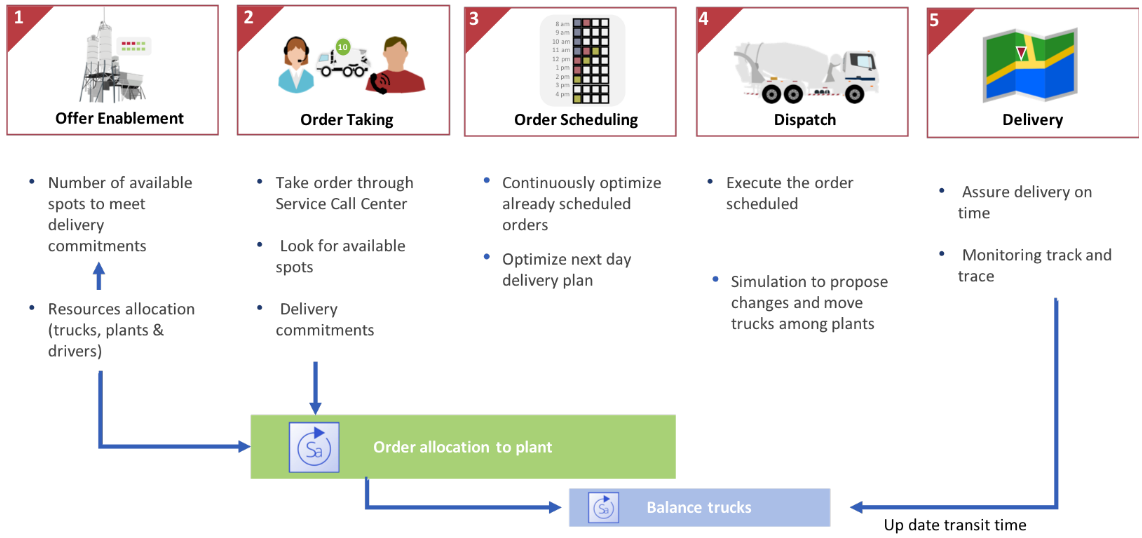


Figure 5.1: Diagram of the implementation the dynamic tool in the order taking and fulfillment process.

be re-assigned based on the customer's needs in an hourly basis using this dynamic tool. The features that include the engine are delivery planning, monitoring of load compliance, dynamic evaluation of truck optimal origin, assessment of startup compliance, monitoring of plants, and geographical visibility of plant allocation. Import and export data instructions are not part of this work, since they are explained in the user manual documented by Lozano [18], and Human Machine Interface variables by Navarro et al. [37]. The proposed dynamic tool can be divided into two parts, first an order allocation for each plant and then the on-time balance of trucks in all the company. Therefore, the tool allows to have control of each of the plants based on the filling capacity of each plant and the distances to customers. The diagram of how this engine contibute to the operation process is presented in Figure 5.1.

An example to illustrate how the engine works is presented thorough Figures 5.2 to 5.4. In this example, the delivery to be loaded at minute 440 is synchronized with its corresponding transit time (30 minutes). All of this happens for all the plants at the same time (see Figure 5.2). Three conditions need to be meet to move a loading minute to the loading stock, and at the same time, a truck is moved to the

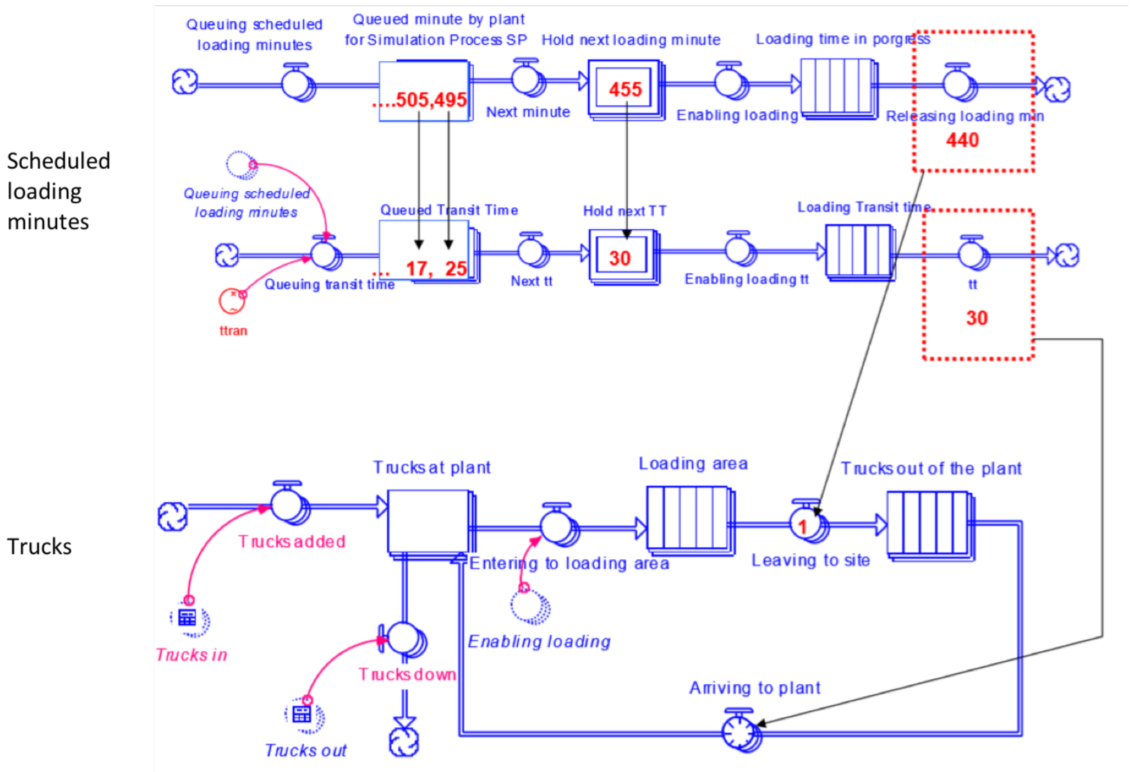


Figure 5.2: Illustration of the I THINK tool to load in minute 440.

loading area (see Figure 5.3). The first condition is that the loading point is free. The second is that there is an available truck at the plant. The third one is that the simulation minute needs to be equal or greater than the loading minute. The attributes of every delivery (i.e. scheduling loading time, transit time and m^3) move simultaneously through the model (see Figure 5.4).

The objective of the order allocation is to obtain the loading schedule of each plant to efficiently attend every client in a day. As the clients usually request more than one service, we consider a discretization of the whole day in minutes to reduce the scale of the problem. The output of the engine is an ordered sequence of minutes for the scheduled loading time in each plant to attend on time at each customer. To overcome this problem, a stock and flows model is used with a ordered queue. The order in the queue of each service depends on its scheduled loading time. The loading minute is establish based on verified conditions of execution and to generate

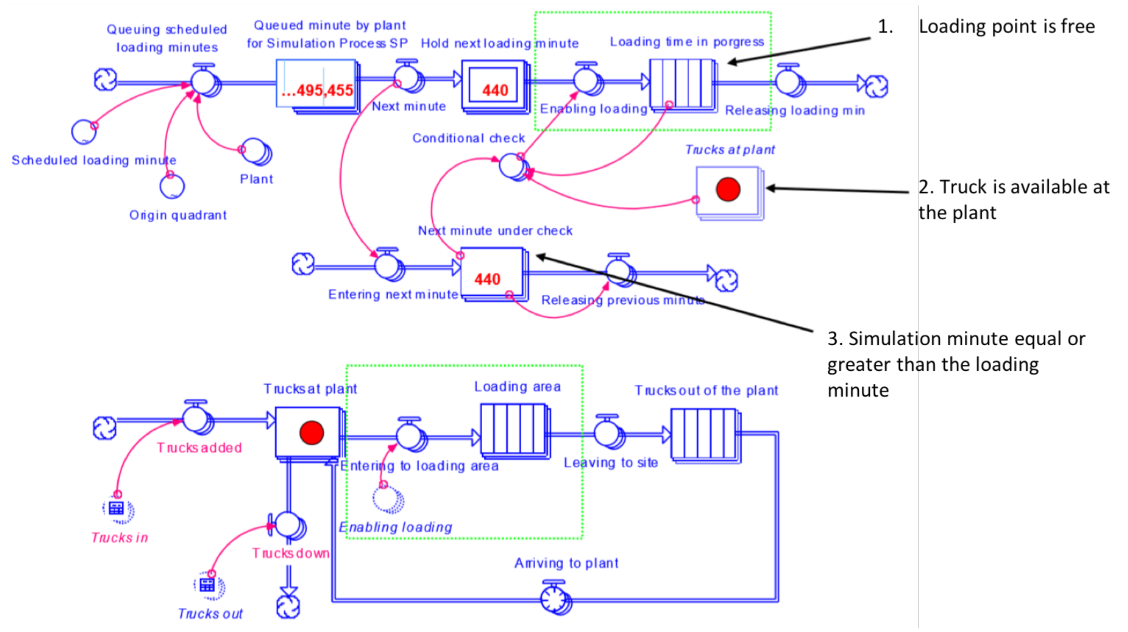


Figure 5.3: Conditions to meet for move a truck to the loading area.

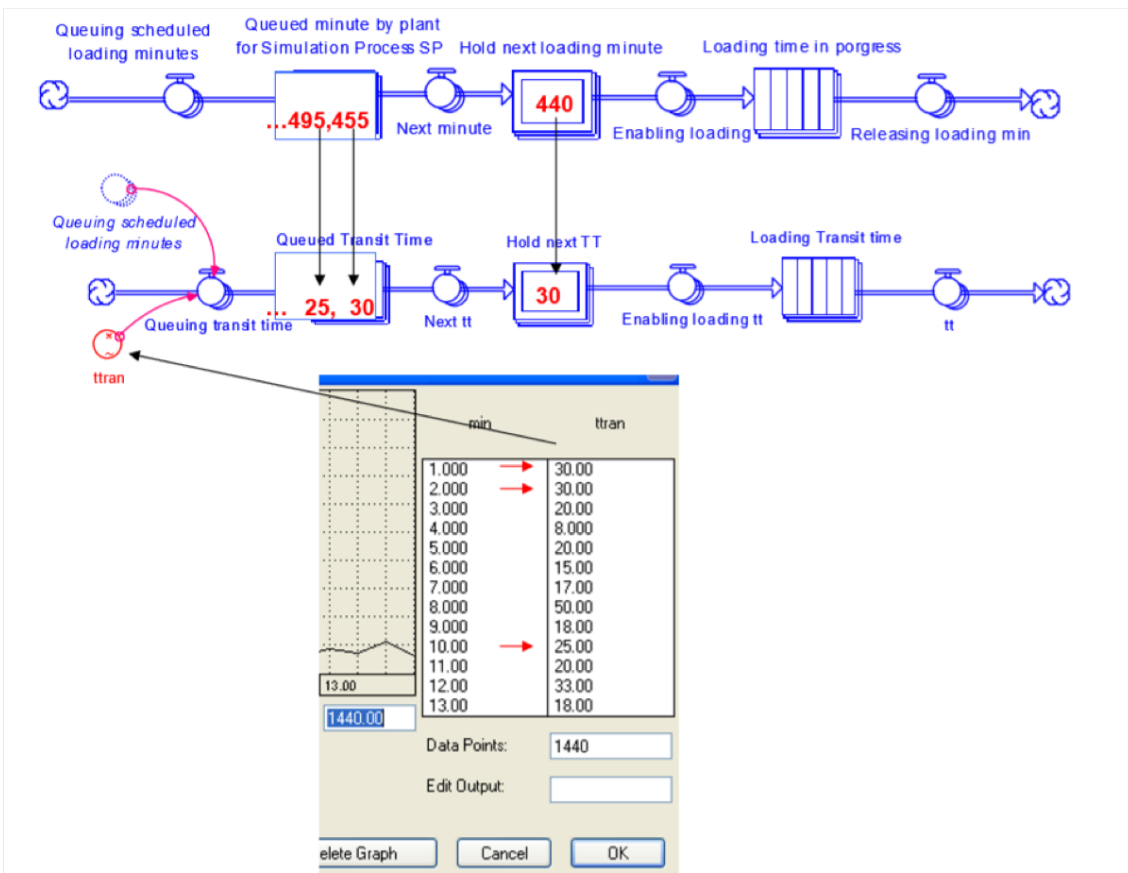


Figure 5.4: Example of the attributes of every delivery.

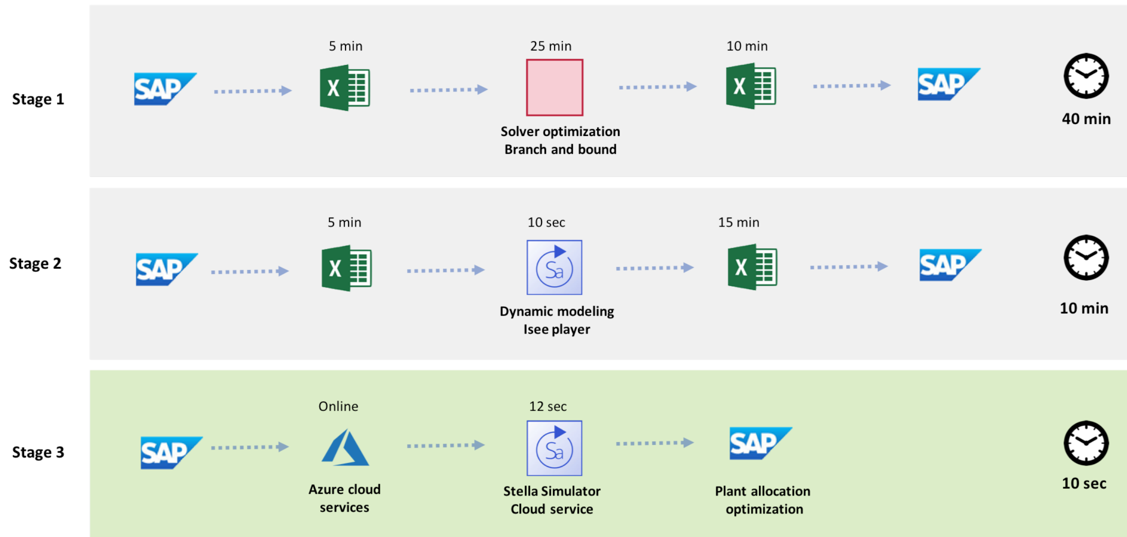


Figure 5.5: Time comparison of three stages of the implementation of order allocation engine.

synchronization signals for parallel processing on order information. To estimate the theoretical-loading time of each service it is considered, depending on the customer, the loading time and the travel time[1] from each plant to the customer service. The travel time is synchronized with the truck for each plant's services with the information of loading minute and volume through the simulation time. The cubic meter values are also synchronized to its loading and travel times. The scheduled loading minute is synchronized with the actual loading time. To establish the theoretical-one loading minute that is based on none consideration of execution conditions, and to count the number of services scheduled from the transactional database in a day. Execution conditions of free loading area and truck availability are ignored. The reduction in time for implement the order allocation in the company is shown in Figure 5.5.

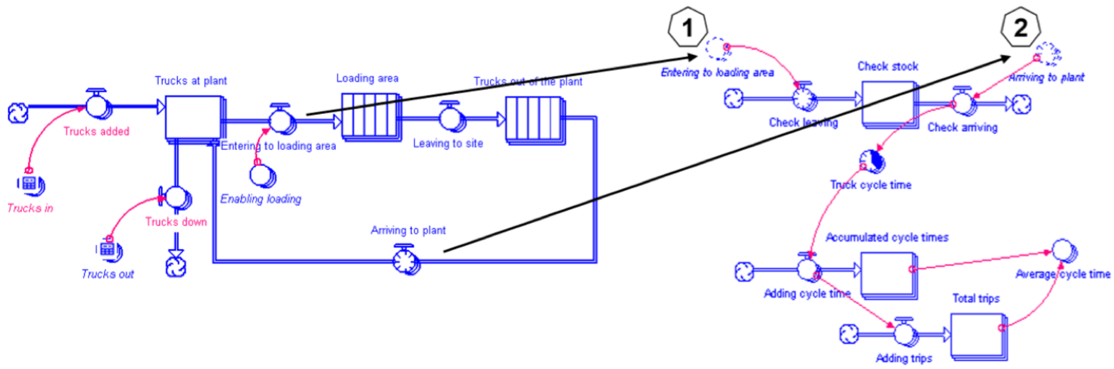
The on-time balance of trucks considers the amount of trucks necessary to load each service is considered as it is the limiting resource. It is considered the time of attention and cycle of each plant, a procedure to know how many trucks have been

[1]The travel time is estimated using Google Api's.

assigned and how many are missing according to the demand of customers. During each round, the process begins by reviewing the trucks assigned to each of the plants according to the demand of the customers. The following indicators for truck allocation performance by simulation are considered minutes of trucks' stay at plant, minutes without trucks in each plant, and required trucks per hour. Average cycle time are computed at each plant by average times obtained by Google Maps. An example of how to calculate the cycle time is presented in Figure 5.6. The time delay for the real process is obtained to register the delay in minutes between the actual loading time and the programmed loading time and to establish the greatest delay hourly. The delayed trucks in the simulation process are account to establish the amount of services delayed per hour by simulation. Also, it is register the minimum amount of trucks available per plant in the course of each hour by simulation. The truck waiting minute at plant for the Real Process is estimated from trucks actual stay at plant, the minimum number of trucks required in each plant, and minutes of plant without trucks. To establish the actual loading minute that is based on the free loading area condition. The condition of truck availability is ignored. The actual loading minute is considered then to count the number of services fulfilled in a day. The reduction in time for implement the order allocation in the company is shown in Figure 5.7.

5.2 Machine Learning Techniques

As mentioned by [22], Machine Learning Techniques are intended to look for an alternative to doing what is already done by experts in RMC dispatching rooms. To implement this idea, we consider a wide range as suggested by [22] of supervised machine learning techniques. The training data includes how the expert decide which clients is attended by which plant in the ready-mixed concrete delivery problemon



Average cycle time is calculated from the minute the truck starts loading (1) until the same truck gets back to the plant (2):

- Truck starts loading at minute 440
- Journey time from plant to job: +30 min
- Unloading time at the customer: +15 min
- Journey time back to the plant: +30 min
- Truck is back to the plant at minute 515

For this load, the cycle time is 75 min

Figure 5.6: Example to calculate the cycle time.

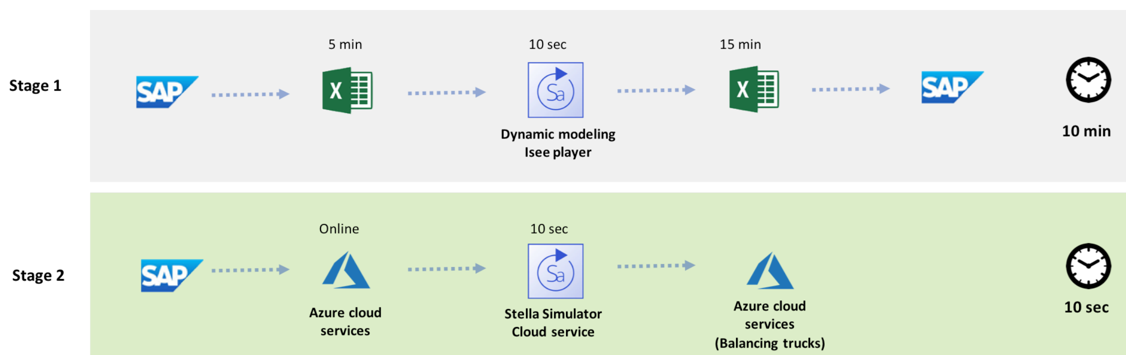


Figure 5.7: Time comparison of three stages of the implementation of balance truck allocation engine.

day-on-day operations. In operation, the experts decision are account by interpreting all the relevant information of customers, plants, traffic, and availability of resources (vehicle fleet, capacities), among others attributes. The company policy that experts follow is that their need supply of all customers with the available resources and keep all the customers pleased. In particular, the dataset shows the experts decisions in several circumstances, low demand, medium demand, and high demand. Therefore, it is expected that Machine Learning techniques will match the experts decisions.

The dataset includes a total of 127 days from real day-on-day operations of four months, from August to November. From these days, a total of 302 559 jobsites are considered. The parameters of each of the jobsites used to construct the training and test datasets are the following, based on [22]:

- Day of delivery in the week (Monday, Tuesday, . . . , Sunday).
- Volume of delivery (m^3).
- Expected arrival time at customer (hh:mm).
- Longitude of customer.
- Latitude of customer.
- Total number of received orders in day.

The model used for each of the techniques is $y = f(x)$, where y represents the experts decisions about a selected plant for each delivery to a jobsite, f is the Machine learning technique (Classifier), and x are the input parameters for each jobsite.

Each of the Machine Learning approaches try to classify objects that belong into a dataset into categories based on attributes on the objects. To adapt this concept to the ready-mixed concrete delivery problem, the categories are represented as the plants and the objects to be classified as the customers/jobsites. Therefore, the classification problem becomes an allocation problem, because it is desired to know the assignments of the plant to attend to each customer according to their attributes.

5.3 Case study: Ready-Mixed Concrete Delivery Problem

Effective production scheduling and efficient truck dispatching are significant issues for a carrier's ready-mixed concrete plant and construction site management. Also, the carrier need to address both timeliness and flexibility, while at the same time satisfying construction site operating constraints. As it is mention in previous chapters, in the concrete industry, the delivery problem has a dynamic environment and involves constant changes, mainly in the dispatch of services causing a mismatch of what planned delivery times and most of the time generates customer dissatisfaction and money losses in the company.

The company needs to generate quick and alternative plan solutions to act before any variation of the establish schedule occur due to one (or more) of the possible causes presented previously. These solutions robust as the decision makers, with their expertise, are able to find the best solution that this improves the current schedule, in terms of diminishing the global cost and trying to deliver on time each service. This include a no interruption of delivery of trucks to a client, or at least maximize the number of customers to attend. In addition, since the problem persist during the day, it must be executed several times to react on time. Therefore, this work focuses on solving the concrete delivery problem of a local concrete company. The company has 22 plants to serve a total of 1 000 customers a day. The amount summation of orders for these customers yields a total of 4 000 m^3 a day. In Table 5.1 are shown the most important, by experts opinion, parameters to consider in the ready-mixed concrete delivery problem. The company practices overbooking to protect itself from those customers who cancel a large volume of concrete. Even with all these resources, the company is unable to meet the demand on a regular day.

At the present time, production and dispatching scheduling work is done manually based on the decision-makers's experience, a method which is neither effective nor efficient. Therefore, a tool is needed to control and visualize what is happening so that they can not attend to all the clients as they should.

Table 5.1: Most relevant parameters of the some ful-day analysis.

day	Number of plants	Number of clients	Number of services	Types of concrete	Total volume (m^3)
1	21	66	111	68	1250.3
2	21	68	108	75	1563.3
3	22	75	104	80	1481.3
4	20	70	105	71	1554.3
5	22	65	96	69	1436.3
6	21	56	81	61	940.7
7	22	78	110	75	1027.0
8	21	76	115	79	1216.2
9	21	65	95	67	1304.1

The term *first-round* has taken on significance to both the concrete company and their customers. The schedule of the dispatchers are more accurate at the beginning of the day, before the dynamic environment begin to impacts their plan. Hence, customers who are typically on-schedule are more likely to place orders during first-round and are more likely to be accepted (due to the fact that customer service representatives take into account historical behavior when accepting orders). Likewise, dispatchers take great pains to ensure that drivers arrive at first-round customer sites on time. As a rule-of-thumb, the dispatchers consider the end of the first-round to occur at 9:00 a.m.

Due to the complexity of the problem, it was decided to study it by components which involve strategic, operational and real-time decisions, similar to that studied by Lourenço et al. [17] and Durbin [7]. These components are: the *order entry planner*, the *arrival time planner*, the *next day planner*, the *real-time planner*, and the *real-time dispatcher*. The following sections describe these individual components, as well as the utility of these components to the *customer service representatives* and dispatchers of the company.

ORDER ENTRY PLANNER The order entry planner is the first stage. It focuses on customer service. An order is taken from each client and according to the load availability of the plants it is decided if the order can be taken or it is sought to agree a schedule that is beneficial to the client and the company. Customers can order with a maximum of three days in advance, orders with less than two days are rarely occurred by clients with special requirements but in the majority of the cases are not accepted.

ARRIVAL TIME PLANNER The arrival time planner is the second phase. This phase focuses on determining the arrival of the next day's operators according to the demand planning for that day and takes into account the number of services that will be available during the first hours of the day, the load capacity of the plant and the frequency of customer service, as well as the return times to the plant of each truck. It is assumed that all orders of the following day have been accepted and do not undergo any change.

NEXT DAY PLANNER The purpose of the next day planner is to generate the best concrete delivery plan according to the volume of the orders of each client, the limitations of overbooking, the load capacity of the plant and the distances to customers of each plant. Make three plants: one, two and three days. For the next day the plan is generated at the end of the day, this in order to capture any changes that could have had some order from customers. First, the demand planning department is responsible for generating a concrete delivery plan for one, two, and three days.

Real-time Planner The real-time planner have direct collaboration with order entry planner since they have to see what spaces are available during the following days to be able to accept an order. Customer services normally exceed the capacity of a truck. Therefore, the service is splited into the number of orders required to fulfill that service. The company has at this moment a person being next day planner and real-time planner at the same time.

Real-time Dispatcher The real-time dispatcher consists in assigning the trucks to the construction sites complying with the delivery plan made the previous day. It is required to continually update the schedule for orders currently in progress as well as for orders that are within the local time-horizon under consideration (typically 2 hours). The real-time dispatcher does this on a continuous basis due to unpredictable schedule changes that occur throughout the day, hence it needs tools that allow monitoring the location of the trucks throughout the travel and thus be able to detect easily if they comply with the established and otherwise react efficiently. Next, the dispatch department is responsible for manually planning and scheduling concrete deliveries, these includes assigning the trucks to the works in addition to monitoring the positions of the trucks. Finally, the renegotiation department, which is recent, negotiates the schedule of services with those clients to which it is not possible to meet with the established delivery schedule.

In the next chapters, results and discussions on different analysis, experiments are presented to validate how the use of the engine can help the dispatchers and planners to increase its effectiveness.

Chapter 6

Results

In this chapter, it is presented the optimization analysis of the schedule in the decision support engine used to help planners and dispatchers in a dynamic environment is presented. The characteristics of different instances, by days, such as running-time, size, among others are addressed. As mention in previous chapters, on day-to-day operations, dispatchers require good and credible recommendations of the schedule but it is no necessary to give an optimal solution due to problem size. Nevertheless, a fine tuning, using experts opinions, was performed to better match the business plans of the concrete company. The dispatchers does not measure run-time or can recognize divergence of optimality. Therefore, as the engine results are in reasonable short time and yields similar results to the expected,, the dispatchers support and accept the engine as a day-on-day tool. This acceptance permits to shift from truck-based dispatching to a more efficient scheme, the demand-based dispatch. In the following sections, a summary of the metrics is presented.

6.1 Scope and Limitation of the Analysis

The analysis focuses on two components the next-day plan (NDP) and the real-time dispatch (RTD). The planner runs the NDP in a batch mode, at the end of the day, to generates a schedule plan for the next day. It is considering the overbooking. The dispatcher runs the RTD in real-time every round, that is three times a day. The engine solves a time-window horizon of the in progress orders and all orders that will begin within the next round. A typical day includes 300-400 deliveries utilizing a fleet of 80-120 trucks loading concrete from 20-21 plants. Other parameters setting are listed in Table 5.1. For every day, the parameters considered are the number of plants (capacity), the total number of clients, the number of services, how many types of concrete are produced, and the total volume of concrete in cubic meters (m^3). In Table 5.1 are presented only those parameters with higher impact to the company, according to experts opinion. As the optimality is not considered by the planners and dispatchers, the engine performs an heuristic procedure returning the best solution founded by the analysis of different scenarios. The time to return a complete optimization of the entire schedule is in reasonable time (less than 20 seconds), permitting to the dispatcher analyze the results with sufficient time before the concrete is shipped.

6.2 Analysis of Schedules

To further understand the results of the NDP and RTD, the evaluation of the schedule is required. As mentions before, the schedule analysis of NDP begins in the previous day and the RTD begins by evaluating first round assignments. The analysis of schedule is performed by round, and whole day, depending if it is the planner or the dispatcher who is performing the analysis. The planner makes the analysis of the whole day and the dispatcher makes the analysis every round.

The performance measures to consider are *compliance* and the *cost of operation*. Compliance refers to arriving at the delivery time agreed with the customer; arriving with a difference of thirty minutes (positive or negative) of the planned delivery time is considered that the schedule has been fulfilled, on the contrary to overcome the difference of thirty minutes is considered a breach in the agreed delivery schedule. The cost of operation includes the costs of using trucks (approximately seven Mexican pesos per kilometer).

One of the desired variables to control is the usage of a truck, the longer the better. For example, if a truck is assigned trips from a different plant than the optimal, the truck will make fewer trips by spending more time on journeys and will visit fewer customers during the work day of the operator. In the company it is known that a truck must make at least four trips in a day to be profitable. By improving the allocation of trucks that are in origins that are not optimal, each truck that improves its origin will have more time available to serve a customer and may arrive on time with more probability than not being assigned to its optimum plant.

Two main limitations are those that prevent adjusting to the schedule agreed with the client: the trucks and the load capacity of the plant. If there are no trucks available at the loading time to attend a customer, it will not be possible to arrive on time with the customer due to the lack of trucks. On the other hand, if you have trucks in the plant but the loading places are occupied it will not be possible to carry out the load generating a delay in the order which prevents arriving at the agreed time with the client.

6.2.1 Next Day Plan

As seen in Table 6.1, the NDP can review the solution in less than an average of 20 seconds to evaluate the next day. The engine considers real (truck capacity) and phantom trucks (theoretical trucks) to deal with overbooking and cancellations. Through experimentation with parameters, the assignment of how many trucks are needed to the first round for next-day scheduling was determined. In addition, it has a subsequent analysis of the evaluation of the planned assignment against the one that actually occurred. We select the instance with greater number of services to illustrate the analysis of schedule. The analysis is performed for each loading hour, from 8:00 a.m. to 18:00 p.m. The ten hours where the plants have consistent demand. It is considered the schedule of the previous day of the established loading hour, the schedule at the established loading hour, and the schedule one hour after the established loading hour. To exemplify the problem of schedules in the United Kingdom of one of the countries where the company is present. This country is selected due to the information availability, but the problem and characteristics are encountered in other countries where the company have plants. In the example, the names of the plants are the same used by the company but the presented values have been modified multiplying by a factor. The data is taken from a real-operation day.

Figure 6.1 shows an increasing filling pattern for order taking as services arrive to the whole company reaching the available limit one day before the operation. Normally two days before there is no space and there are availability problems. Due to the natural variability of the process, on an operational day cancellations and changes in schedules are likely to occur. Therefore, in a global perspective, the company always be at 80 % of its maximum capacity. Analyzing this information and taking it as a reference for operation leads us to misleading conclusions since the level of aggregations is global and there are no considerations for plant level.

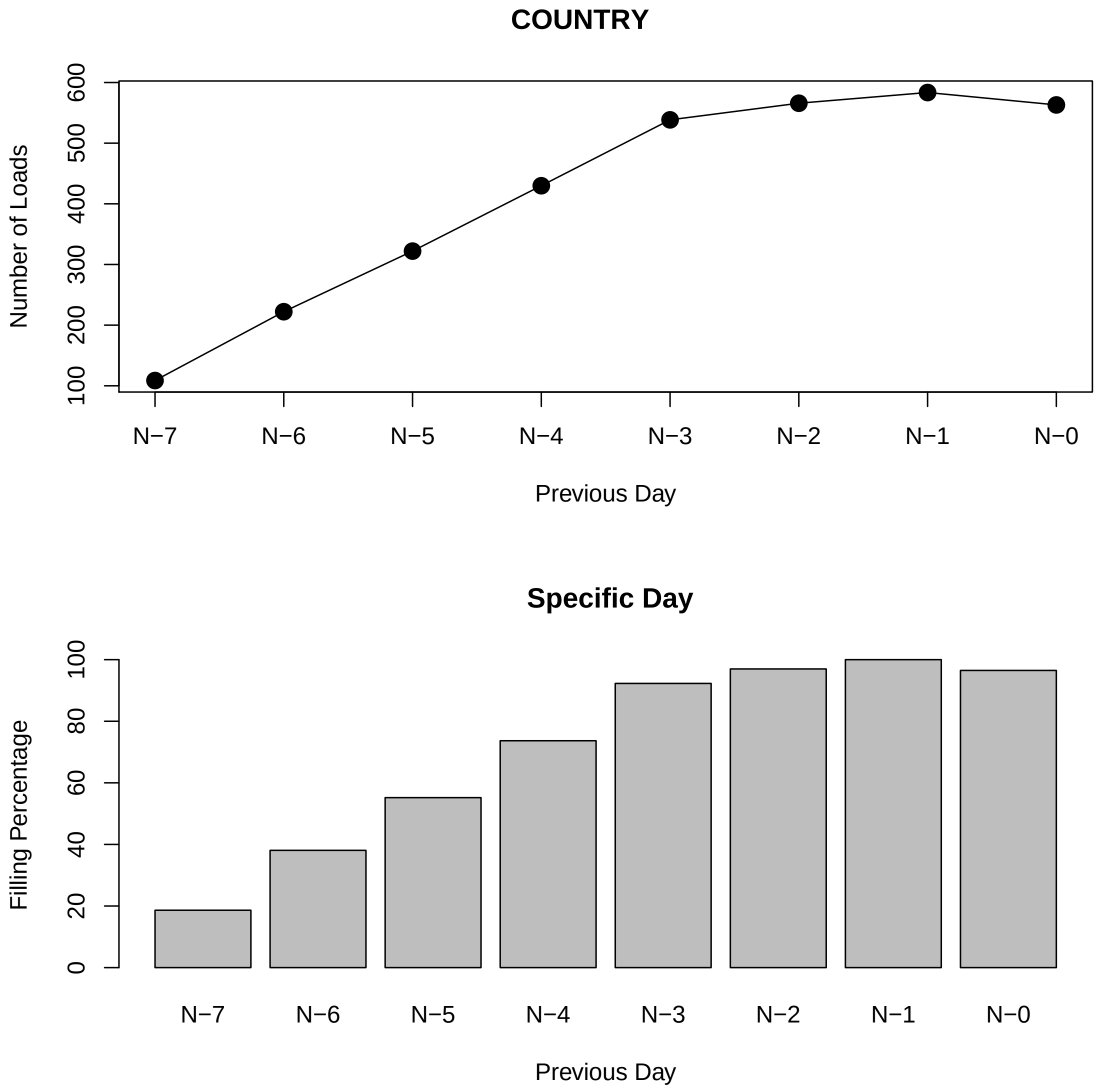


Figure 6.1: Global fulfilment.

The overbook that a particular day in a company level is up to 10% but searching at the plant level it can be over 90% or even 100%. When a desegregation is made at the plant and hour level, we can no longer see this same stable behavior as in the company level. This has worried planners and dispatchers since they use the pre-existing tools and do not rely on it.

In the Figures 6.2 and 6.3, it is analyzed for each hour of the operating day. And each of the lines indicates previous days of order taking. In these figures we

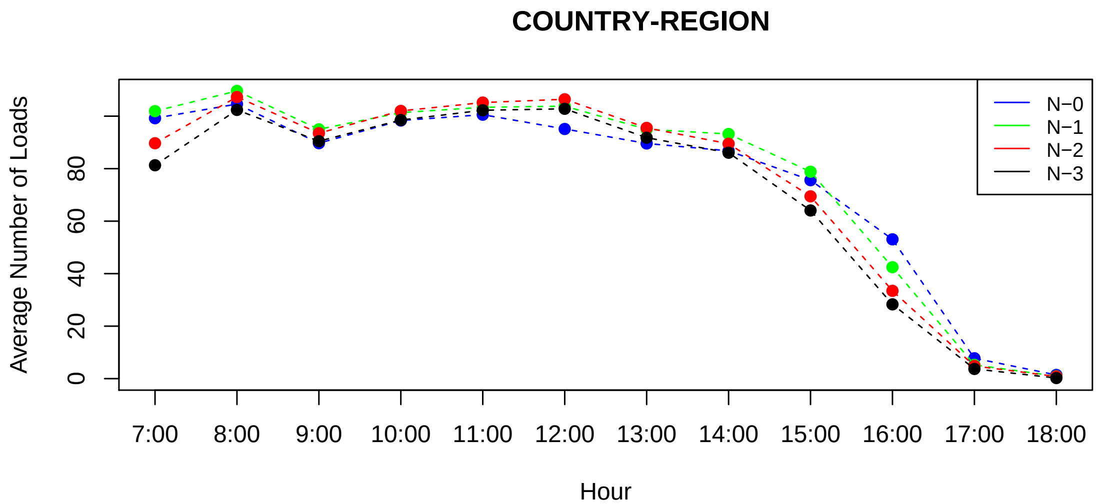


Figure 6.2: Global fulfilment by hour $n = \{0, 1, 2, 3\}$ previous days.

can see which are the hours of greatest demand. In the morning there is a greater number of orders in the afternoon it becomes more stable and at night the number of services begins to fall. This is natural process behavior for a company level.

To analyze different plants, we will only take two types as reference. A plant with higher demand (volume) and a plant with a low volume of services. In the plant with the largest volume (see Figures 6.4 and 6.5), the behavior is similar to that observed when we do the analysis at a total level. This is because plants with higher volume have very stable elements due to the amount of services that are assigned to them. There is little or no variation that allows deviation from the data. On the other hand, when observing a plant with little volume (see Figures 6.6, and 6.7, 6.8), we begin to see differences and variations that are due to poor decisions in ordering. There is no consistency in the filling, although the expected growth is observed, it has variations that are not natural to the process and taking order-taking practices as a reference generates a distrust of operators.

Due to the problems presented, which the planners and dispatchers have been aware of since before the use of the tool, it is proposed to have information on how the status of each plant is several days before the execution in order to realign and readjust all the variation. natural process.

6.2.2 Real Time Dispatch

The dispatcher generates the results by round. Therefore, the dispatcher focuses on loading all orders that are in progress and begin to prepare for those orders that comes in the next hour. The orders that the dispatcher needs to be review, in the busiest time of the day, can be up to 50 orders in progress with another 10 to 20 that start in a time window of the next hour or two. Every time the engine runs, the size of the problem is reduced as many orders finished from past deliveries, that is because there is no need to reassign those orders.

The results, for a sample of the whole days analyzed, is presented in Table 6.1. In Table 6.1 are shown the most important variables to track by the dispatchers. The engine gives to the dispatcher the numbers of services that needs to be change, the traveled distances as it is schedules and the traveled distance by using the optimization, and the cycle time reduced. In the days analyzed, an average 11% of services needs to be change by the optimization. In average, these results represent a saving in 9.5% in travel distance resulting into reducing by at least 2 minutes the cycle time of trucks. Therefore, from the point of view of the the dispatchers these savings are used to help and improve its decision making. The dispatcher can select from different alternatives depending on what is happening in the day as the engine did not consider external environment as weather or traffic.

As illustration purposes, we present only the analysis of the day with most services, that is the 8-th day. In this specific day, there are 15 changes proposed by

Table 6.1: Results of the optimization on the schedules for the selected days.

day	Number of services with change	Travel distance original (km)	Traveled distance improved (km)	Savings improve (%)
1	8	4090	3836	6.21%
2	6	3795	3543	6.64%
3	12	4103	3961	3.46%
4	15	4723	4082	13.57%
5	10	3349	3184	4.93%
6	10	3938	2830	28.14%
7	13	3319	3098	6.66%
8	15	3620	3307	8.65%
9	15	3802	3507	7.76%

the engine. As illustration, in Figure 6.9 show the view that the dispatcher sees in the interface. In the interface, a table is shown for each order. In the table, all orders that needs to make changes are considered, the original assigned plant, the optimal plant assignments plant, what product it is considered, how many cubic meters are in the order, by how many trucks needs to be delivered, the benefit (in minutes) of the change, some actions to perform (view on the map, accept or reject), and the status of the change. The green filled cell represent those orders that reduces the expected traveling time and the red filled cells represent those that increases the traveling time. These increasing in traveling time by changing an order to other plant is necessary because, if we consider all changes, there are more benefits and therefore the traveling time is reduced. In this day, by performing all changes a reduction of 8.65% of traveling distance is obtained.

6.3 Engine Plant Analysis

The following are the four charts that explain the performance of the relevant variables for each plant.

SERVICES LOADED PER HOUR GRAPH Figure 6.10 represent the number of services per hour. It consists of four variables:

1. **Demand:** Demand of services that have to be load. Is located in Quadrant [3,4].
2. **Simulation:** Are the simulated number of services loaded. Is located in Quadrant [1,1].
3. **Real:** Real number of services loaded. For actual or past scenarios. Is located in Quadrant [1,4].
4. **Capacity:** Is the plant capacity of services per hour. Is located in Quadrant [4,3].

In Figure 6.10, the upper right side shows the hour of the simulation. The user can change it to look forward.

TRUCKS PER HOUR GRAPH Figure 6.11 shows every minute the number of trucks in the plant. It consists of two variables:

1. **Trucks_at_Plant_SP:** Are the simulated number of trucks in the plant. Is located in Quadrant [1,2].
2. **Real_truck_at_plant:** Are the real number of trucks in the plant. For actual or past scenarios. Is located in Quadrant [4,3].

FULFILLMENT AND ACCUMULATED DELAY GRAPH Figure 6.12 shows the value per hour of the services loaded and the accumulated delay. It consists of three variables.

1. **Fulfilled_SP:** Percentage of fulfilled services loaded.
2. **Fulfilled_RP:** Percentage of the real fulfilled services loaded, for actual or past scenarios.
3. **Delay_by_SP_Plant:** The accumulated delay in minutes of the load.

Average waiting graph Figure 6.13 shows the stay in minutes of the trucks in plant, or the minutes they wait to be loaded. It consists in two variables:

1. **Waiting_minute_SP:** Is the simulated stay in minutes of the trucks in plant. Is located in Quadrant [1,2].
2. **Real_waiting_min:** Is the real stay in minutes of the trucks in plant, for the actual and past scenarios. Is located in Quadrant [4,3].

In Figure 6.13, if the value of stay is high the plant has an over load of the trucks, or low demand of services. If the stay value is low the plant has little o no trucks to fulfill the demand.

6.4 Comparison with Machine Learning Classifiers

This section, first shows the performance in a real dataset from the company under study of different Machine-Learning techniques. Then it shows the performance comparison of the proposed approach using system dynamics with different Machine Learning approaches. The Machine Learning approaches are selected as [22] shows that automating RMCDP by Machine Learning techniques showing good accuracy compared with expert decisions. It is used a data set with real day-on-day operations. To compare with our system dynamic approach we select four classifiers: Random Forest, Decision Tree, k-mean Neighbors, and Linear Discriminant Analysis. To measure the performance of the Machine Learning approaches, we select the accuracy of the results from real data, overbooking of plants, and travel time from plant to jobsites.

6.4.1 Machine Learning Performance for Real Dataset

The results for each of the Machine Learning approaches are presented according by using different percentages of services of the total. Those percentage of services of the total (302,559 services) are: 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 100%. As an example of how it is calculated, the analysis of 10% of 302,559 services available correspond to the 30,255 services are considered as the dataset. If the resulting number of services in the dataset is a fraction is rounded down. For each percentage, the training data is selected as the 70% of the services. The remaining 30% is used for testing. The measure selected to compare is the percentage of correct assignments of services to plants according to what happened in the testing process. This is considers as we want to obtain how good is the model using unknown information.

From Figures 6.14 to 6.16 it is shown the results of accuracy for each of the four machine learning approaches in the different segmentation of the data is presented.

Figures 6.17 to 6.19, the results of overbooking[1] for each of the four machine learning approaches in the different segmentation of the data is presented.

[1]The capacity for each plant does not need to exceed.

As a recapitulation of previous figures, Table 6.2 shows the results for all the scenarios considering each segmentation of days, percentage of data, and Machine Learning approach. Two metrics have been selected for assessing the performance of the selected algorithms. From a general perspective, we select the accuracy to be more the more important feature when a comparison between two algorithms as it expose the ability for each approach to identify the correct assignment (correct class), which is the main objective of the classifier. In terms of accuracy, for percentages of data from 20% to 100%, the Random Forest approach achieve always the best results, follow by Decision Tree, Linear Discriminant Analysis, and last k-nearest neighbor. When the percentage of data is 10%, the best performance is achieved by the Decision Tree approach. The of most of the algorithms are similar For each of the scenarios, the overbooking rates are quite similar. There is no difference which of one is selected, the overbooking remains in similar values of mean and standard deviation. We suspect that the instances where algorithms are slightly different may be due to randomness concerns. Moreover, the approach that outperform, by far, is the Random Forest. This results is the same as the one obtained by Maghrebi [22].

As it can be seen from Table 6.2 and Figure 6.14 to 6.19 , the best result is obtained with the Random Forest approach. Therefore, for next comparison only this approach is considered. From Figure 6.20, the performance of Random Forest approach is shown. The highlights is that by using a greater amount of information (100% of the data) good allocations are obtained, about 75% correct, from customers to plants. In addition, the variation of the average is ± 25%, which indicates that although on average it performs well on most occasions, it does not exceed 50% of correct assignments, which is the same as throwing a coin. A special care must be taken with this result, since assignments are only being made according to what happened in the day-to-day operation without considering the behaviors of previous days. Some of the issues that may not be considered are that some customers cancel

Table 6.2: Results for all the scenarios considering each segmentation of days, percentage of data (%D), and Machine Learning approach: Decision Tree (DT), k-nearest neighbor (KNN), linear discriminant analysis (LDA), and Random Forest (RF).

		Accuracy				Overbooking			
	%D	DT	KNN	LDA	RF	DT	KNN	LDA	RF
Monday to Friday	10%	59.9% ± 31.9%	14.8% ± 25.8%	29.4% ± 33.4%	59.1% ± 34.9%	−0.59% ± 0.35%	−0.63% ± 0.36%	−0.66% ± 0.36%	−0.63% ± 0.36%
	20%	47.2% ± 34.4%	11.2% ± 16.7%	24.4% ± 30.0%	57.3% ± 32.5%	−0.60% ± 0.35%	−0.60% ± 0.35%	−0.61% ± 0.34%	−0.61% ± 0.34%
	30%	48.4% ± 33.1%	14.7% ± 22.0%	23.9% ± 30.1%	62.2% ± 29.7%	−0.63% ± 0.35%	−0.61% ± 0.35%	−0.63% ± 0.34%	−0.60% ± 0.35%
	40%	45.5% ± 34.0%	15.8% ± 24.1%	26.4% ± 32.1%	62.1% ± 30.9%	−0.61% ± 0.35%	−0.64% ± 0.35%	−0.64% ± 0.33%	−0.65% ± 0.34%
	50%	48.3% ± 35.7%	12.2% ± 19.9%	27.3% ± 31.5%	60.6% ± 30.6%	−0.62% ± 0.35%	−0.63% ± 0.34%	−0.65% ± 0.34%	−0.63% ± 0.34%
	60%	50.4% ± 36.2%	12.1% ± 18.8%	30.7% ± 32.7%	61.7% ± 31.3%	−0.65% ± 0.35%	−0.65% ± 0.35%	−0.67% ± 0.35%	−0.64% ± 0.35%
	70%	49.4% ± 35.2%	13.9% ± 21.6%	28.2% ± 31.7%	61.8% ± 31.1%	−0.68% ± 0.34%	−0.67% ± 0.34%	−0.67% ± 0.34%	−0.66% ± 0.35%
	80%	54.1% ± 34.2%	14.7% ± 21.8%	27.5% ± 31.0%	61.3% ± 31.0%	−0.65% ± 0.35%	−0.67% ± 0.34%	−0.67% ± 0.34%	−0.66% ± 0.35%
	90%	52.6% ± 34.0%	14.9% ± 21.5%	29.1% ± 31.1%	64.3% ± 29.7%	−0.65% ± 0.35%	−0.66% ± 0.34%	−0.66% ± 0.34%	−0.66% ± 0.35%
	100%	53.2% ± 36.0%	14.0% ± 20.8%	29.0% ± 31.3%	61.6% ± 31.3%	−0.65% ± 0.35%	−0.66% ± 0.36%	−0.66% ± 0.36%	−0.65% ± 0.36%
Monday to Wednesday	10%	54.8% ± 35.8%	13.7% ± 25.6%	31.9% ± 37.8%	51.7% ± 34.8%	−0.65% ± 0.34%	−0.63% ± 0.34%	−0.66% ± 0.34%	−0.59% ± 0.33%
	20%	41.7% ± 33.5%	12.9% ± 18.7%	24.2% ± 29.6%	54.0% ± 31.1%	−0.58% ± 0.34%	−0.60% ± 0.33%	−0.62% ± 0.33%	−0.60% ± 0.33%
	30%	42.7% ± 33.8%	11.2% ± 16.1%	27.5% ± 29.8%	58.9% ± 27.9%	−0.62% ± 0.35%	−0.65% ± 0.35%	−0.68% ± 0.33%	−0.71% ± 0.34%
	40%	43.6% ± 34.2%	9.4% ± 15.3%	23.5% ± 30.3%	55.9% ± 30.6%	−0.67% ± 0.32%	−0.69% ± 0.32%	−0.69% ± 0.30%	−0.72% ± 0.32%
	50%	46.2% ± 37.1%	11.5% ± 17.7%	25.1% ± 31.6%	55.6% ± 31.0%	−0.65% ± 0.33%	−0.66% ± 0.34%	−0.68% ± 0.32%	−0.66% ± 0.33%
	60%	49.0% ± 37.2%	10.9% ± 18.2%	31.3% ± 32.8%	59.3% ± 31.1%	−0.66% ± 0.35%	−0.67% ± 0.35%	−0.68% ± 0.34%	−0.67% ± 0.35%
	70%	50.3% ± 35.1%	13.5% ± 22.6%	29.4% ± 32.6%	60.7% ± 31.2%	−0.66% ± 0.34%	−0.69% ± 0.34%	−0.68% ± 0.34%	−0.67% ± 0.35%
	80%	57.3% ± 36.6%	14.5% ± 22.6%	27.9% ± 31.1%	60.6% ± 31.1%	−0.66% ± 0.35%	−0.69% ± 0.33%	−0.68% ± 0.33%	−0.69% ± 0.35%
	90%	54.3% ± 34.3%	14.0% ± 22.4%	28.6% ± 30.6%	62.5% ± 30.4%	−0.67% ± 0.34%	−0.69% ± 0.33%	−0.68% ± 0.33%	−0.68% ± 0.35%
	100%	50.1% ± 31.9%	12.5% ± 20.0%	26.0% ± 29.6%	58.9% ± 31.7%	−0.64% ± 0.38%	−0.67% ± 0.36%	−0.67% ± 0.34%	−0.66% ± 0.36%
Thursday to Friday	10%	41.3% ± 33.4%	12.0% ± 18.4%	39.9% ± 41.4%	51.3% ± 29.3%	−0.62% ± 0.37%	−0.60% ± 0.36%	−0.63% ± 0.36%	−0.61% ± 0.36%
	20%	41.4% ± 35.2%	12.7% ± 17.2%	22.2% ± 27.5%	48.0% ± 30.6%	−0.55% ± 0.33%	−0.55% ± 0.33%	−0.57% ± 0.32%	−0.56% ± 0.32%
	30%	46.0% ± 33.2%	13.5% ± 19.3%	26.4% ± 28.8%	54.1% ± 33.2%	−0.55% ± 0.35%	−0.57% ± 0.35%	−0.59% ± 0.35%	−0.57% ± 0.35%
	40%	48.8% ± 36.6%	16.6% ± 22.0%	28.2% ± 33.1%	57.5% ± 32.3%	−0.53% ± 0.35%	−0.57% ± 0.35%	−0.58% ± 0.35%	−0.56% ± 0.35%
	50%	56.0% ± 32.6%	14.0% ± 19.5%	26.0% ± 32.0%	58.5% ± 30.1%	−0.60% ± 0.34%	−0.59% ± 0.34%	−0.59% ± 0.34%	−0.57% ± 0.34%
	60%	58.7% ± 33.0%	13.1% ± 19.8%	28.2% ± 31.1%	58.9% ± 29.5%	−0.65% ± 0.34%	−0.60% ± 0.34%	−0.60% ± 0.34%	−0.59% ± 0.34%
	70%	56.1% ± 36.6%	12.0% ± 19.5%	28.1% ± 30.8%	60.2% ± 30.4%	−0.63% ± 0.35%	−0.62% ± 0.34%	−0.61% ± 0.34%	−0.61% ± 0.35%
	80%	51.1% ± 34.9%	13.8% ± 20.0%	26.5% ± 30.6%	58.1% ± 30.4%	−0.63% ± 0.34%	−0.64% ± 0.34%	−0.62% ± 0.33%	−0.62% ± 0.35%
	90%	52.4% ± 32.7%	14.1% ± 21.0%	29.5% ± 31.1%	58.2% ± 32.2%	−0.60% ± 0.34%	−0.62% ± 0.34%	−0.62% ± 0.34%	−0.60% ± 0.35%
	100%	48.5% ± 34.0%	13.7% ± 20.3%	28.1% ± 30.9%	56.0% ± 33.2%	−0.63% ± 0.36%	−0.65% ± 0.34%	−0.65% ± 0.34%	−0.64% ± 0.35%

their orders at least one day before and customers increase the volume of the order during the same day.

Figure 6.20 show the performance of the random forest approach by segmenting the information from Monday to Wednesday, Thursday to Friday, and from Monday to Friday, respectively. In Figure 6.20, it is observed that the segments from Monday to Wednesday and Thursday to Friday, have similar behavior, about 50% of correct assignments, with a variation of $\pm 50\%$. This indicates that there are cases in which no plant is assigned correctly according to the experiences from experts. The best performance is achieved by considering every day from Monday to Friday, reaching a correct allocation of 60%. In terms of variation of the accuracy, the segmentation of days from Monday to Wednesday are higher than any other scenario. Our hypothesis for this event is attributed to the fact that in these days the demand have lower compared with Thursdays or Fridays, and the algorithm does not known how to appropriate allocations when the demand is higher as it is not considered in the training phase of the model. On the other hand, from Thursday to Friday, as the demand is in its higher values, the correct allocation is not good enough when is coupled to the days with lower demand.

In previous figures, only is shown the performance in term of accuracy for the whole company, but if we focus only the plant with the greatest amount of services (historically the plant with higher demand), the variation of the correct assignments increases considerably when using different percentage of data. In Figure 6.21 it is shown the results for this specific plant. According to the results, it would not be recommended to use all the available information (100% of the data) since it has a worse performance (65% of correct assignments) unlike using 90% of the data where up to 80% can be obtained of correct assignments. In both cases the variation has great magnitude, which does not give sufficient confidence to make customer assignments to plants on operational days.

The results in terms of overbooking, for the Random Forest approach are presented in Figure 6.22. The behavior of overbooking, in most of the cases, remains at 0%. A result that mislead, because on an operation day, the plants never overpass their capacity, always stay with the exact capacity or less. We consider that this result is due to the fact that in the analysis only operational data is consider, not previous days when there is an overpass on the plant capacity. For further experimentation, we consider that the combination of data for operational days and assignments of previous days could improve the results.

Also, in Figure 6.22, the worst performance is found when the analysis is performed from Thursday to Friday, where the plants remain at 50% capacity. This results affect the company objectives, as the plants remains with many free spaces that would have served more customers.

The analysis of the Central plant, the plant with greatest amount of services, in terms of the overbooking is shown in Figure 6.23. Figure 6.23 shows this result, and it is observed that the overbooking, on average, is maintained in 0%, that is, the capacity of the plant is respected. Nevertheless, there are scenarios, as the variation is high enough, that obtain a 150% of its capacity and even scenarios where it stays at 50% of its capacity. Both scenarios are not acceptable for the company, overpass the capacity of the plant yield poor customer services as the company does not have the resources to attend all customers. On the other hand, less capacity leaves fewer customers to attend than the capacity on the company.

Finally, one of the most interesting of the achieved results is related to the computing time. This result shows that all of the selected algorithms can solve plant allocation for around 800 customers in less than a second. In the case of using learning algorithms in which the relearning process is being done with a new instance, the computing time also is very small. As mentioned by Maghrebi [22] the ability of machine learning provides us with an opportunity to move toward automation in RMCDP especially when the systems changed and re-allocation must be done. In our case, the results form the machine learning approach can match experts' decisions with an accuracy of around 70%, instead of the 85% of the obtained by Maghrebi [22]. The issue may be due to the problem includes more trucks, more plants, and more customers. Also, human errors in the assignment produce bad classifications. Another possibility is that under some circumstances the experts are free to choose a depot from a list of available depots, and their decisions are mostly arbitrary. This means that whatever choice they perform is considered an acceptable decision. Further experimentation is needed to investigate the feasibility of missclassified instances by using simultaneously optimization algorithms.

In the overall discussion and according to the results shown in this chapter, as the dynamic environment of the elements that need to be considered on the operation day and previous days, it is not recommended to use machine learning algorithms to perform an assignment of the clients to the plants. Not enough percentage is reached to rely on the random forest algorithm when is used in this kind of problem.

For improvements in the percentages of correct assignments of customers to plants, some tool or model that allows to perform an optimization of the resources available the organization is needed. Another improvement of the results may be due to the inclusion of an algorithm to prioritized customers, not only considering the attributes of greater impact, also considering the availability of trucks to assign in a specific time of the day.

6.4.2 Machine Learning versus System Dynamic Approach

Both approaches have small execution time, less than 5 seconds. This characteristic is one of the most desirable as the need to re-run the optimization in the day. Therefore, both approaches are good enough to day-on-day operations.

Friendly interface, easy to use and integrated to SAP. The machine learning approach rely on decision experts to prioritize services based on historical data. In the literature reviewed says that at mini mun, for better accuracy, articles show a total of 4 months is required. On the other hand, our system dynamics approach does not rely on the decision of experts, instead uses all the rules that expert consider to take priorities on the orders, trucks, and plants to improve performance. Also, there is no need historical data.

The machine learning approach decrease its performances as the problem increases. Therefore, only small problem sizes, 4 plants with 40 trucks and a maximum 200 services are solved with acceptable results. Our system dynamics approach has solve grater sizes of the problem. Problems of 20 plants with 130 trucks and around 700 services have been solved.

In terms of priorities, the machine learning approach assign plants to services consider few attributes: day of the week, volume, location. On the other hand, our approach considers all the available information of the client, work, traffic, location, type of cement, type of customer, volume, frequency of service, delivery hours, plant departure hours, and others.

In machine learning approach, 63% of solutions are according to the expert, but on the days considered there are few cancellations and the amount of services is less than 162, approximately 4 times the number of trucks. Around 37% of the results are found to have missclassified solutions appears by differing from the solution proposed by the expert. For these missclassified solutions, about 65% are not feasible.

The machine learning approach does not contain optimization of resources, does not verify plant capacity, if the plants have a similar amount of assigned services (plant balancing). It has not been implemented in an operational situation in a real company. It is mentioned that the integration of optimization models is needed to improve results. Our approach have the possibility of reallocating plants to customers automatically at any time of the day. In addition to assigning trucks to plants, and customers, considering special characteristics of the concrete. Real-time visualization of the plants (capacities, amount of services assigned, type of services, etc.), trucks (load that carries, to which service is directed, time of departure from the plant, estimated time of arrival to service, etc.) , services (following scheduled services, volume, type of cement, customer, type of customer) and traffic (use of maps for visualization). Optimization of resources by balancing services at plants and optimizing the use of trucks to improve delivery times (customer satisfaction). Use of simulation, optimization and dynamics of systems (discrete and continuous events solved by simultaneous deferential equations) to find solutions that meet the requirements of the company and the customer.

Table 6.3 resume the comparison between the machine learning approach and our approach.

Table 6.3: Comparison between Machine Learning (Random forest) and our system dynamics approach (Shaker).

Concept	Random forest	Shaker
Expert Decision	Day-on-day operations	Integrated in the model
Size of the problem	Maximum size 4 plants, 40 trucks and 200 jobs	In operation has been used for 20 plants, 130 trucks and 750 jobs. Maximum capacity 210 plants
Attributes	Weekday, Volume (m^3), Location	Truck capacity, plants capacity, customer type, distance from plant to customer site, concrete type,
Resourse Optimization	No	Yes
Response time	< 1 second	< 10 seconds
Visualization	No	Yes
Real data	Yes	Yes

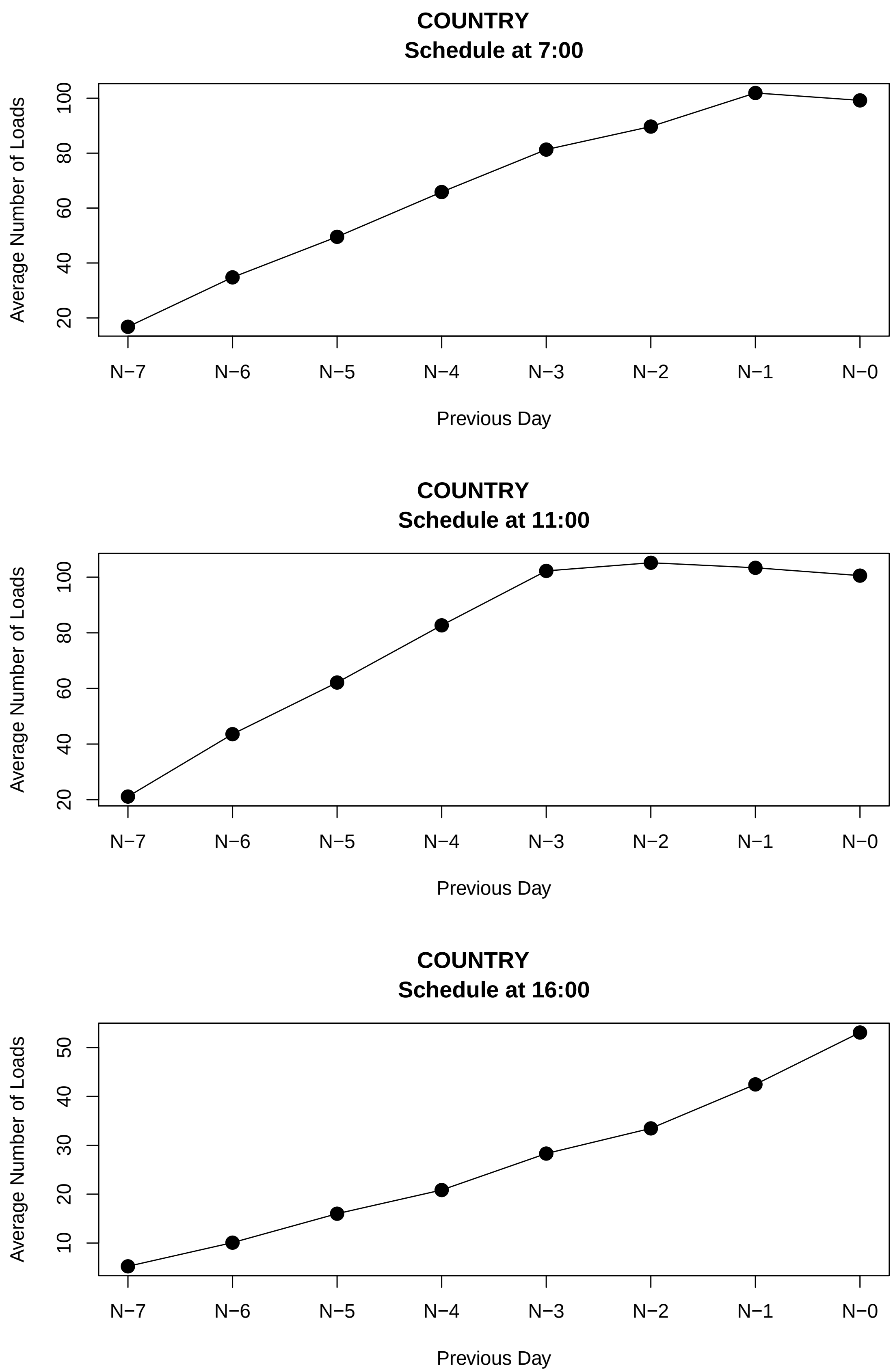


Figure 6.3: Global fulfilment by each hour in previous days.

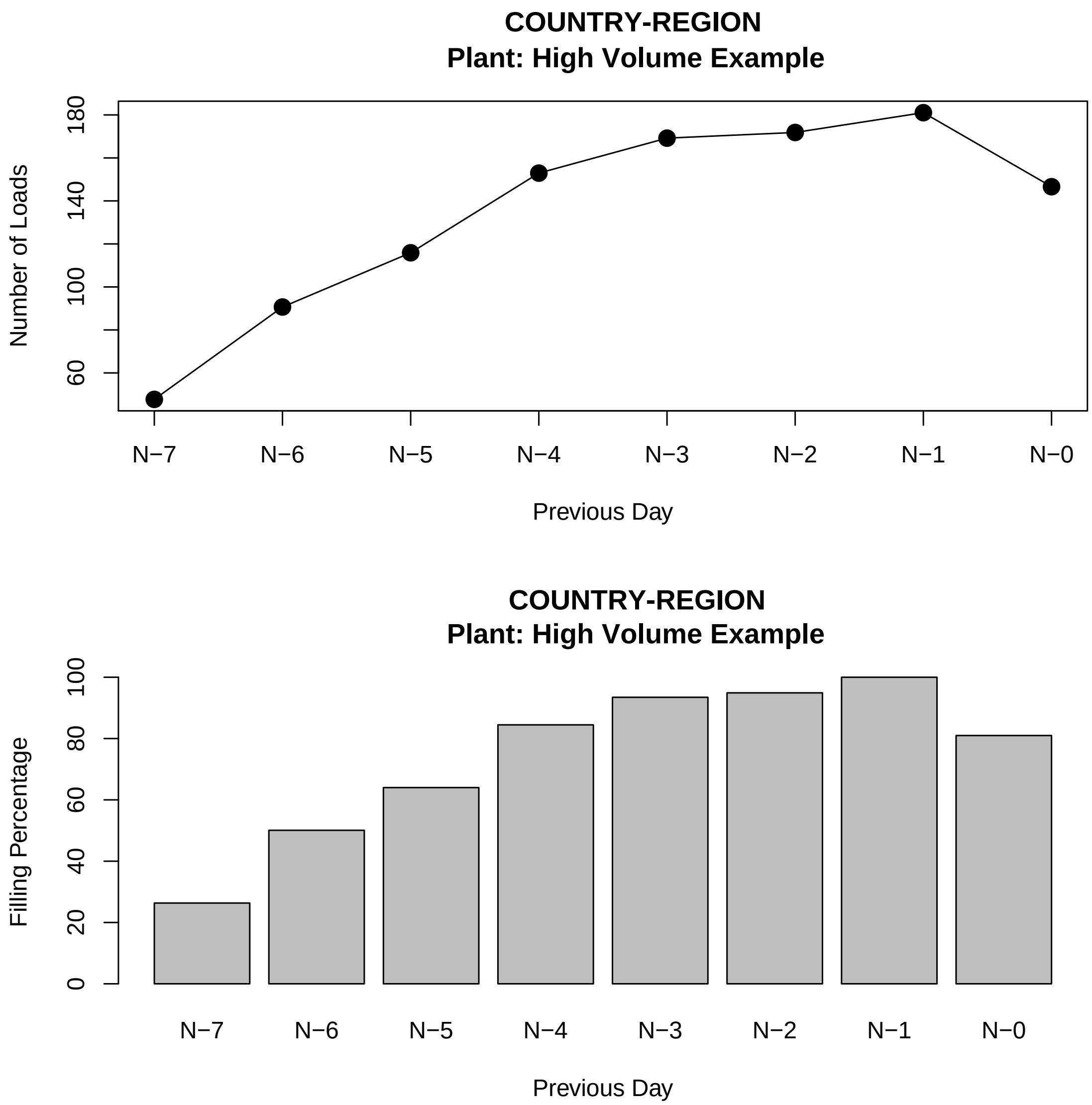


Figure 6.4: Plant (high volume) fulfilment by in previous days.

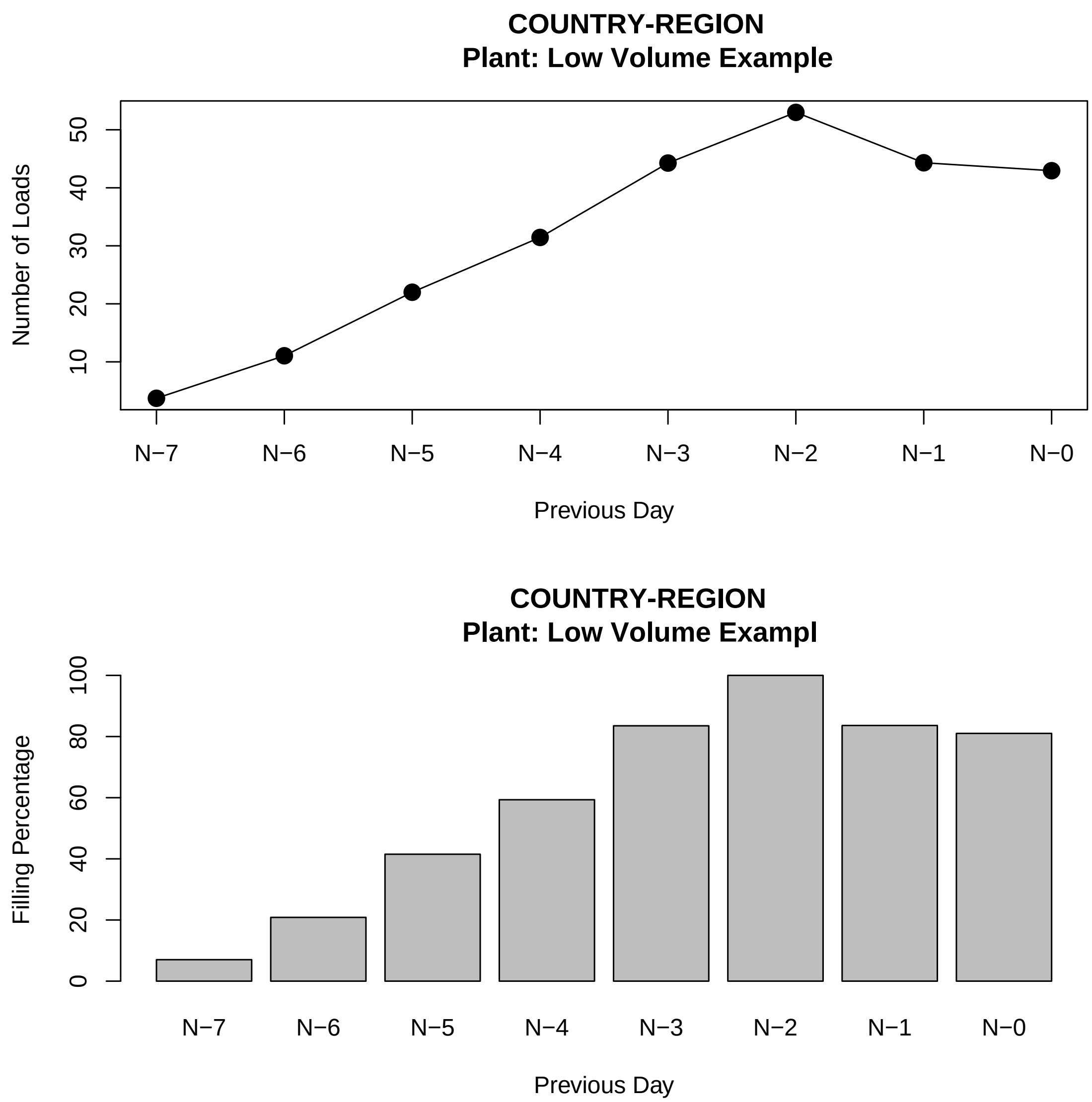


Figure 6.5: Plant (low volume) fulfilment by in previous days.

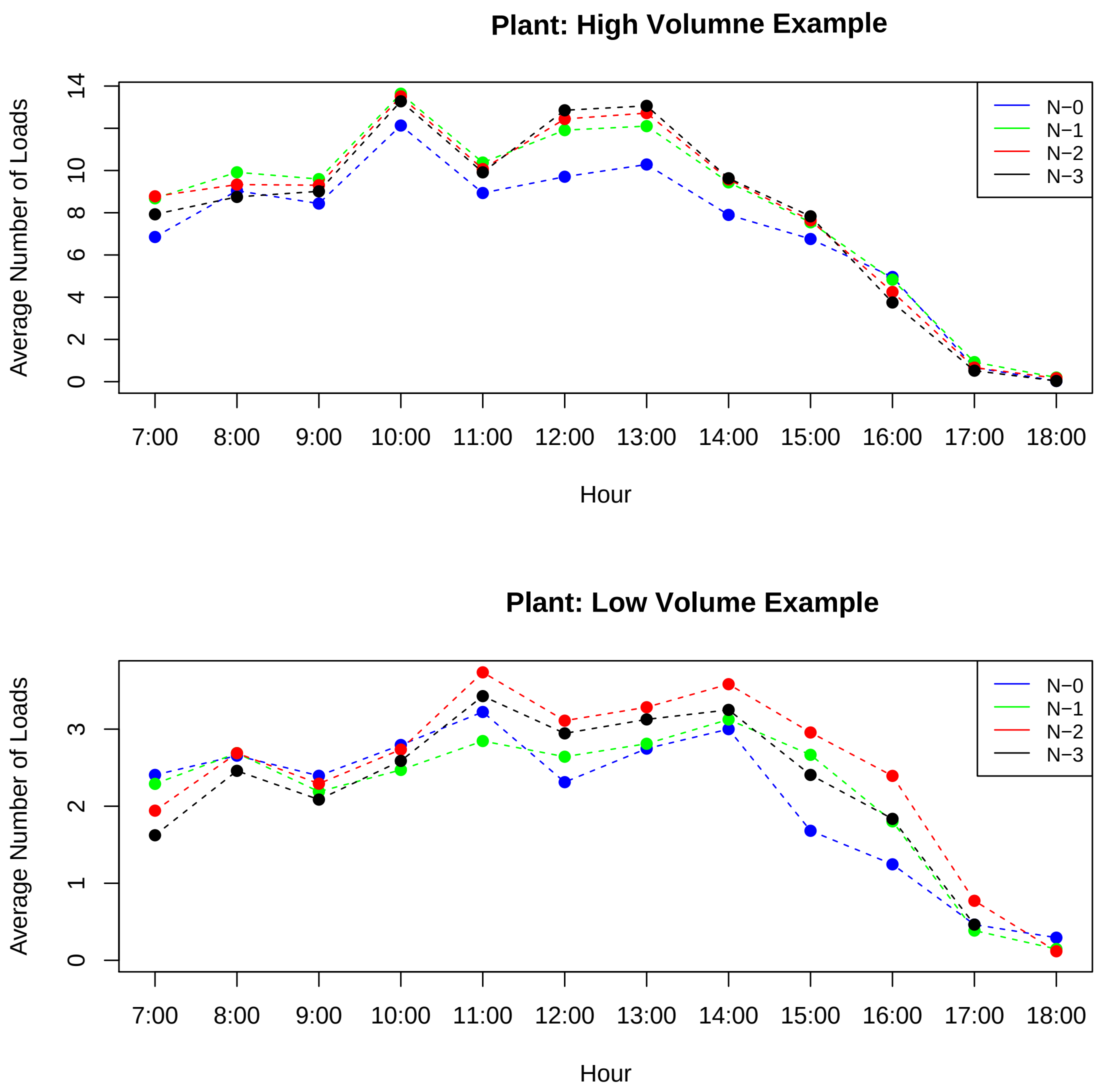


Figure 6.6: Plant fulfilment by hour in previous days.

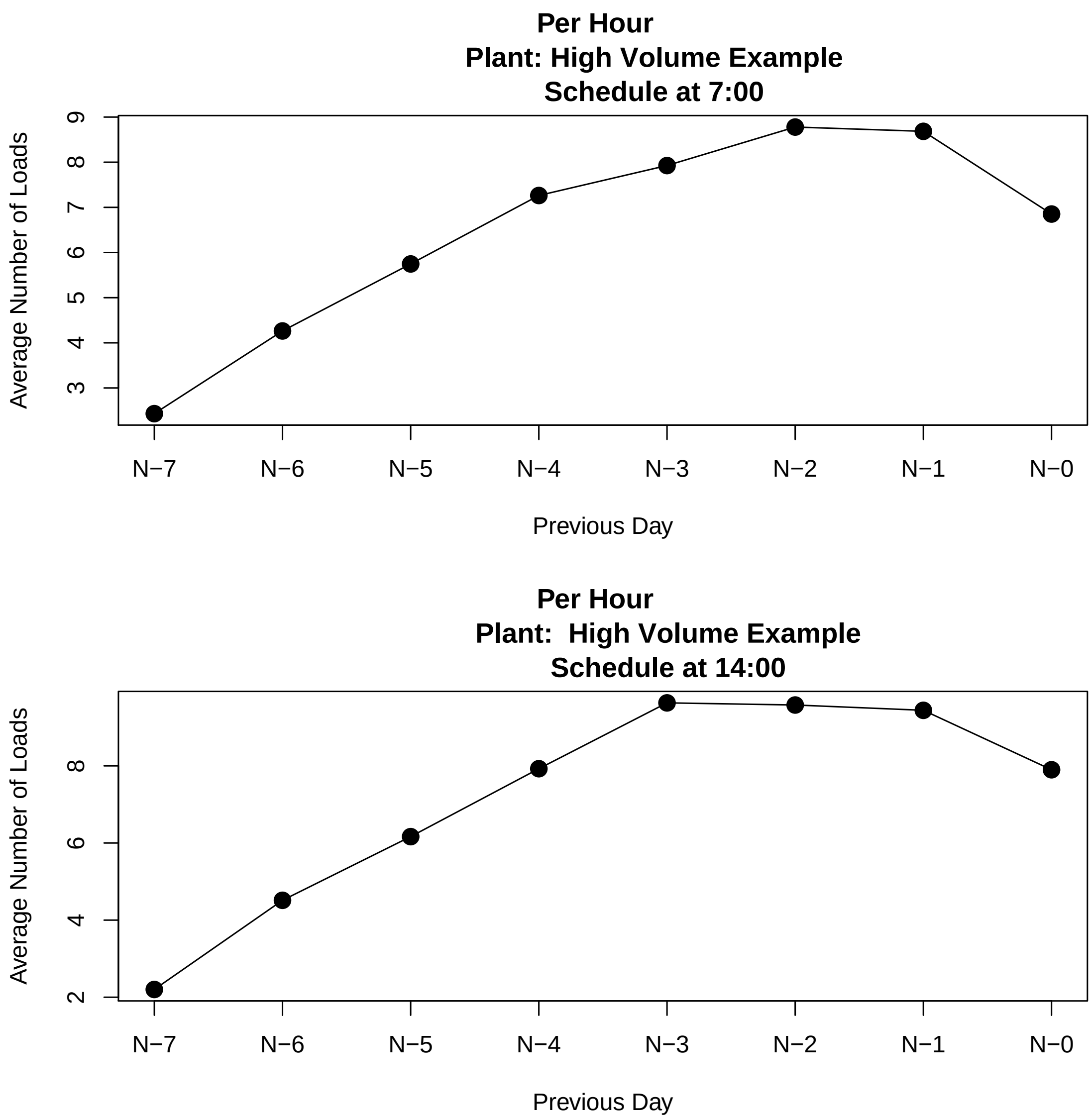


Figure 6.7: Plant (high volume) fulfilment by each hour in previous days.

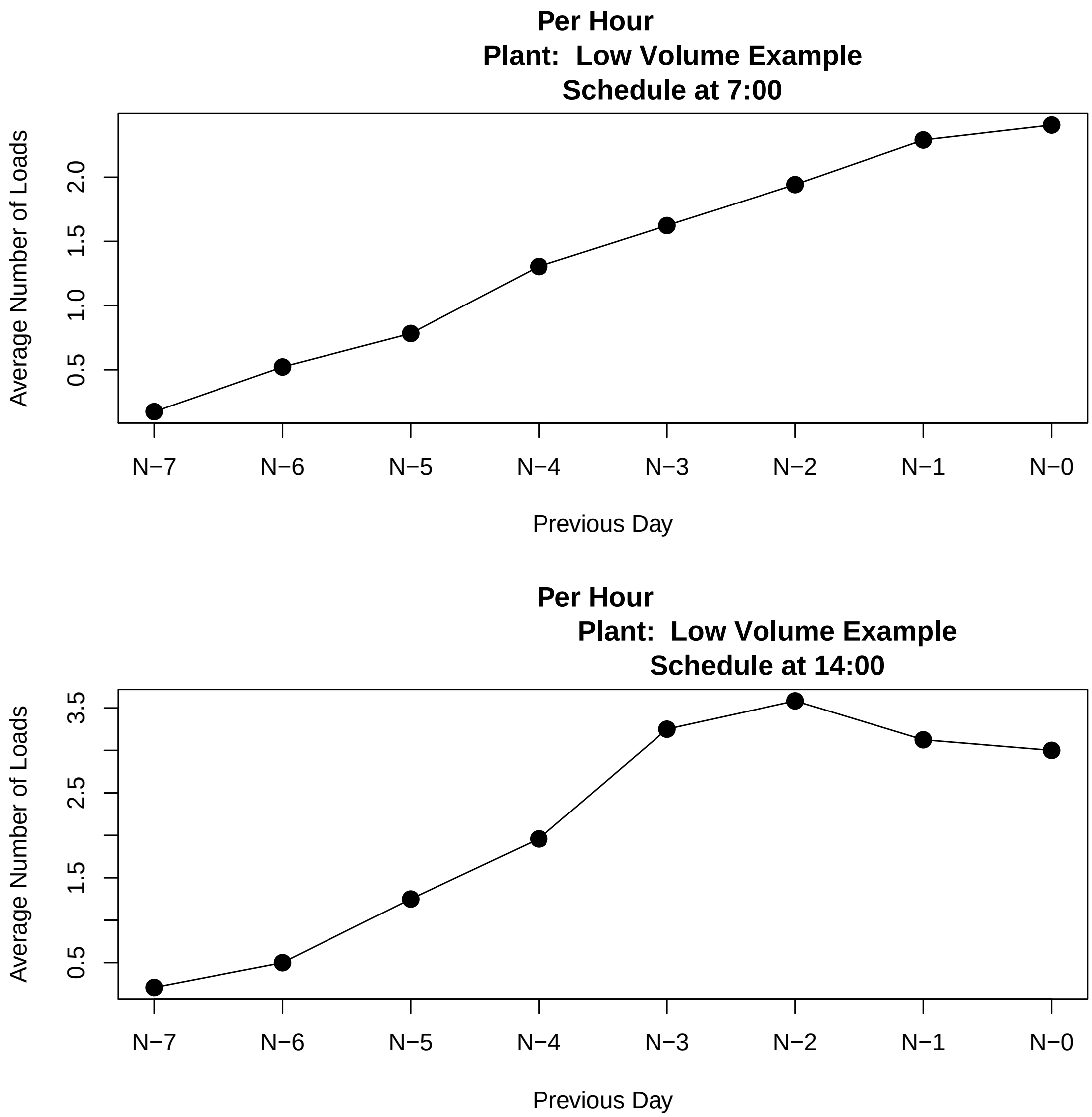


Figure 6.8: Plant (low volume) fulfilment by each hour in previous days.

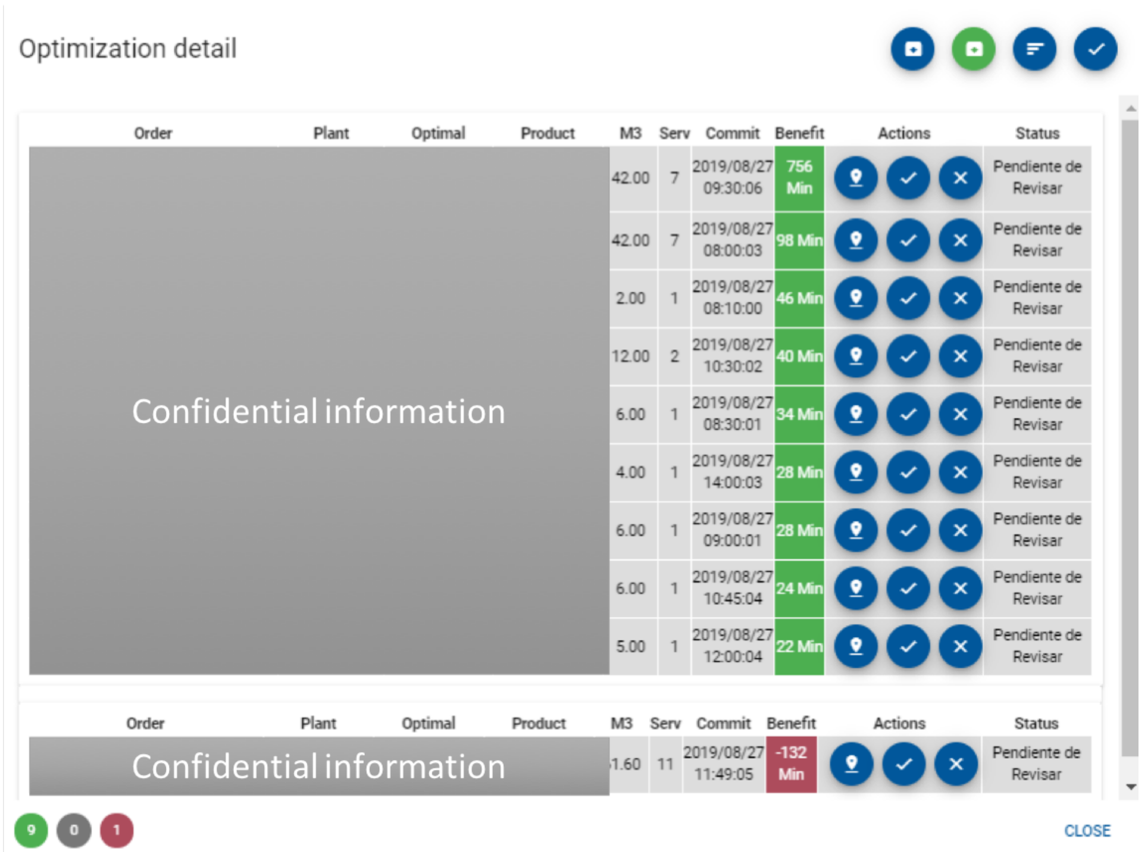


Figure 6.9: Optimization detail view in the engine interface to selected changes in orders. The presented information is for the day with more services.

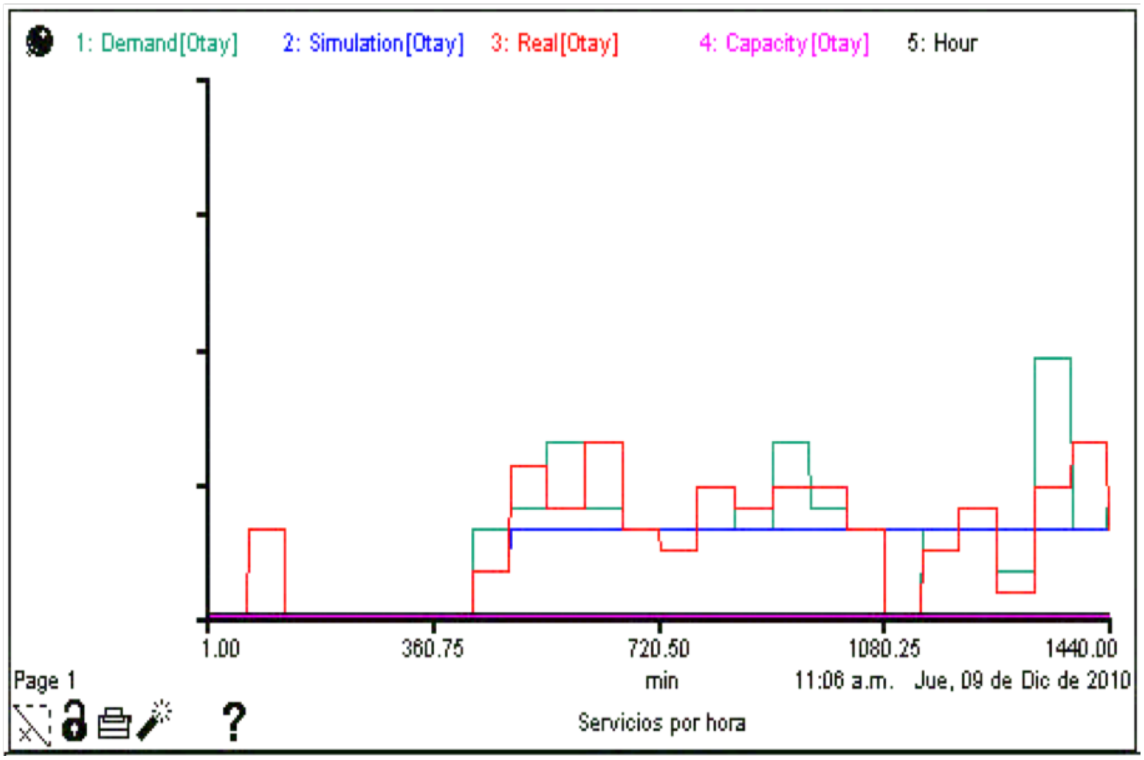


Figure 6.10: Services loaded per hour.

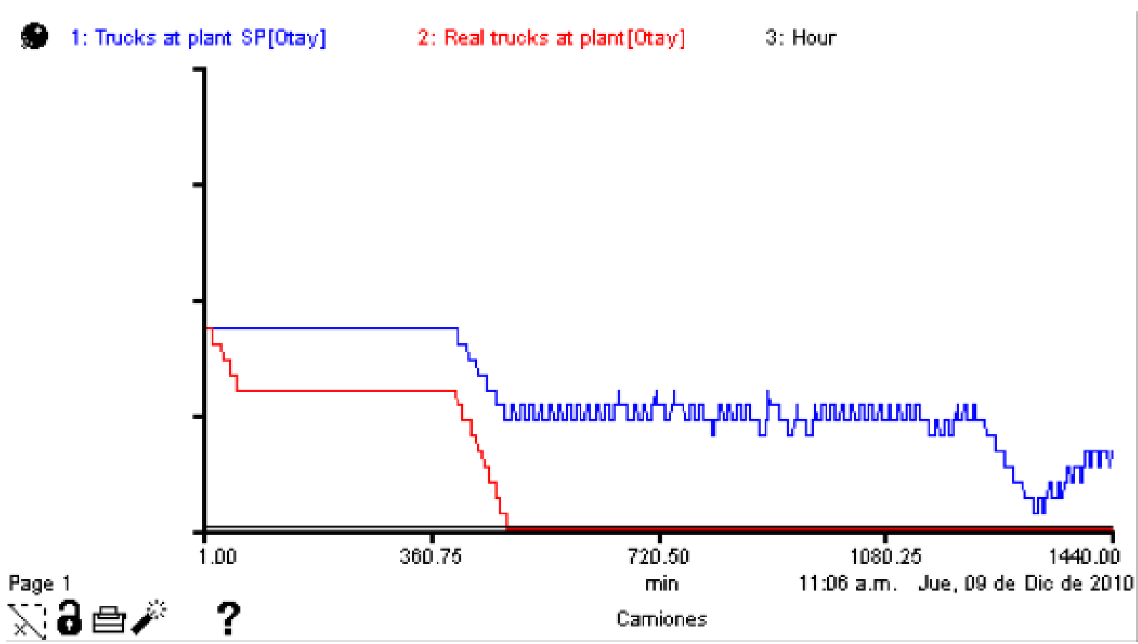


Figure 6.11: Truck at plant.

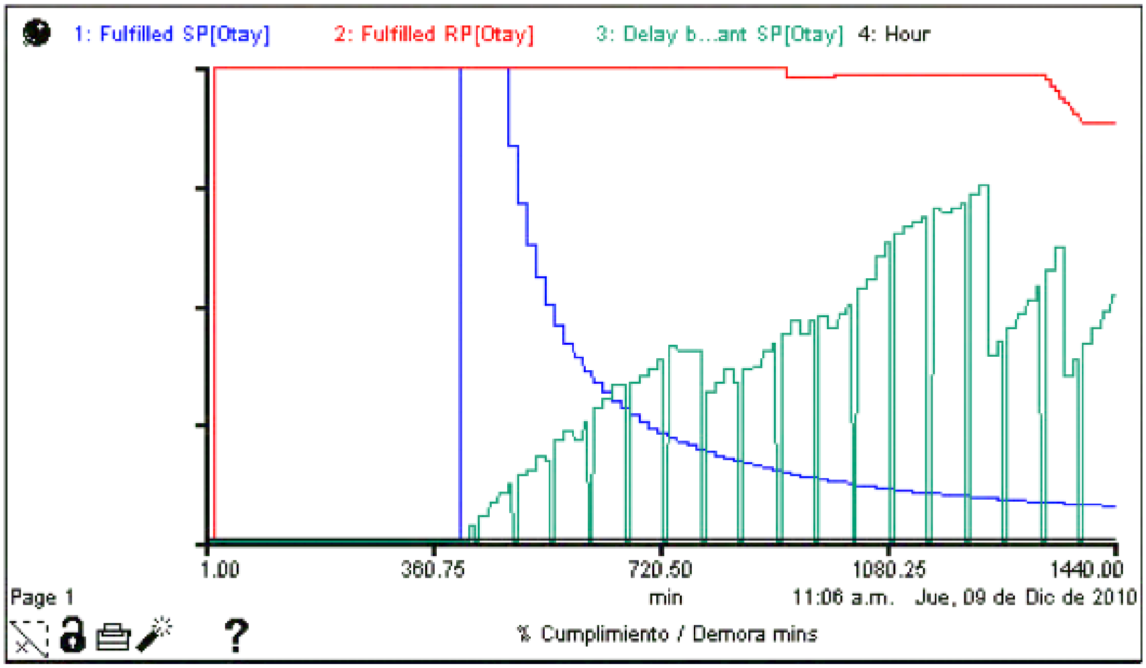


Figure 6.12: Fulfilled Services in a day.

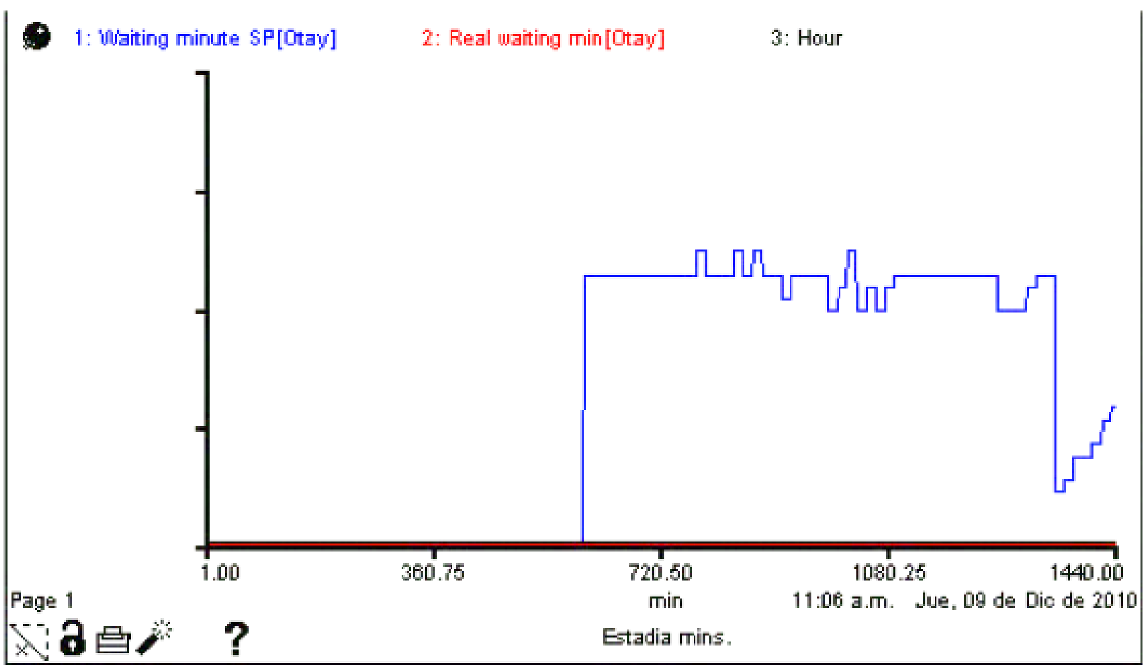
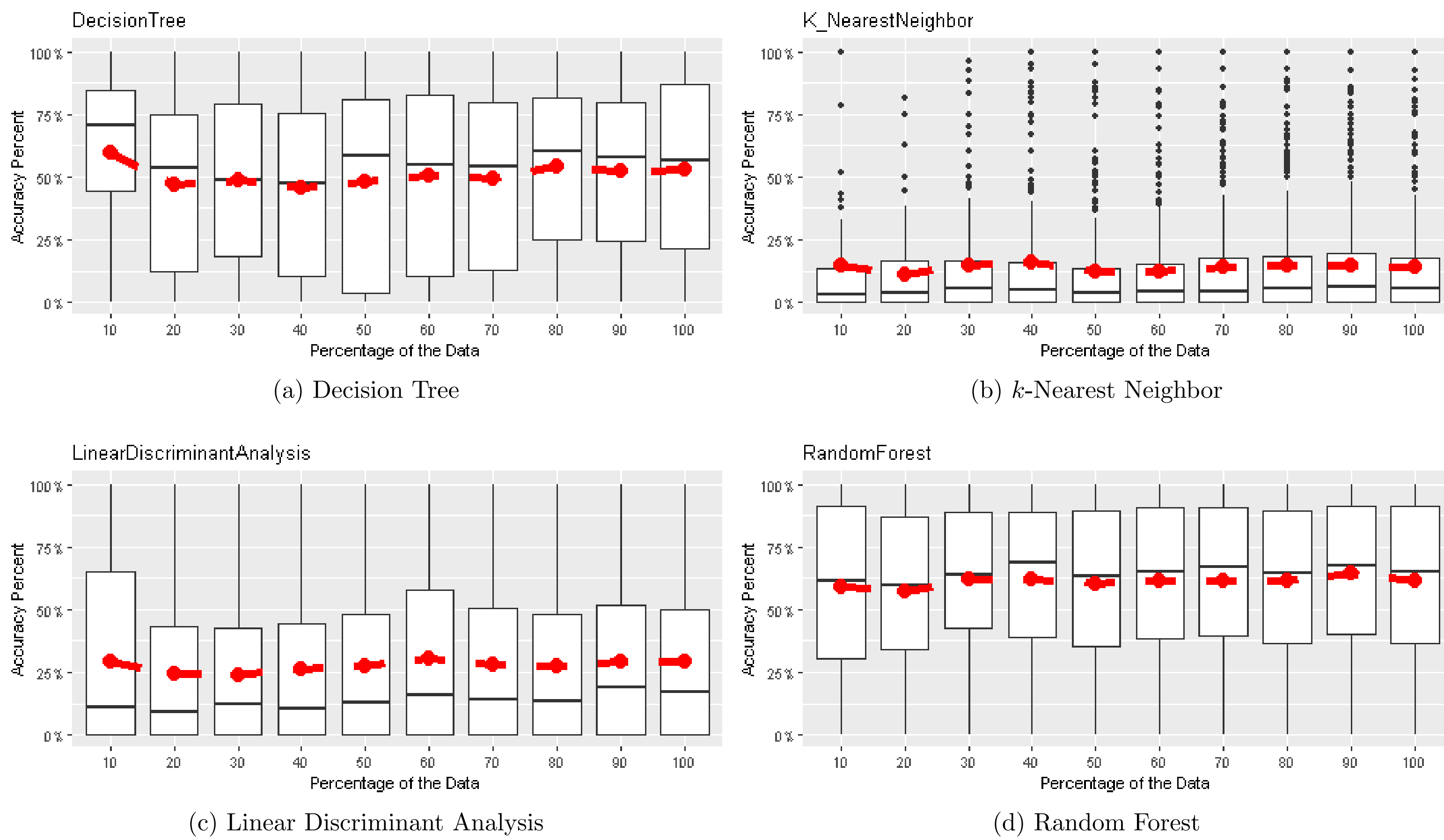


Figure 6.13: Average waiting.



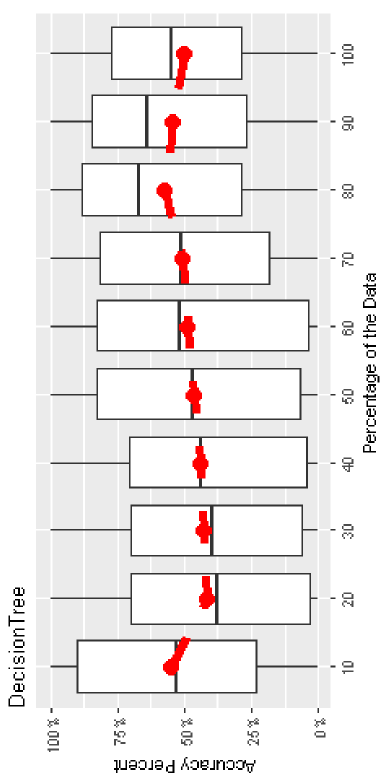
(a) Decision Tree

(b) k-Nearest Neighbor

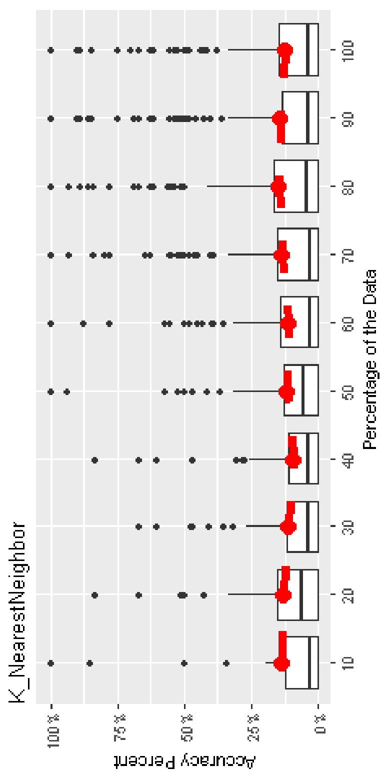
(c) Linear Discriminant Analysis

(d) Random Forest

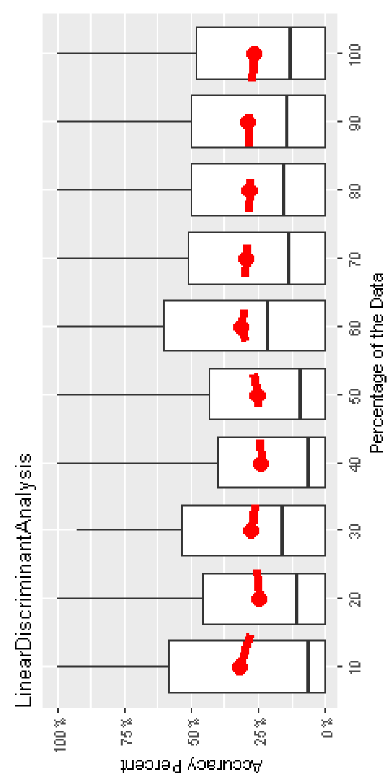
Figure 6.14: Distribution of accuracy obtained from machine learning approaches when data is segmented from Monday to Friday for the four different machine learning approaches (a) decision tree, (b) k-nearest neighbor, (c) linear discriminant analysis, and (d) random forest.



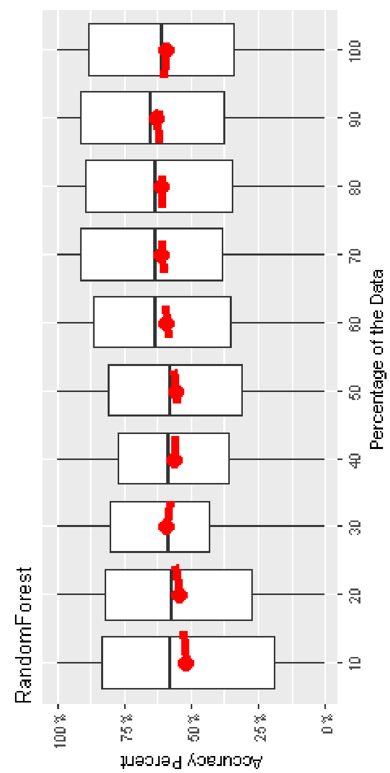
(a) Decision Tree



(b) k-Nearest Neighbor

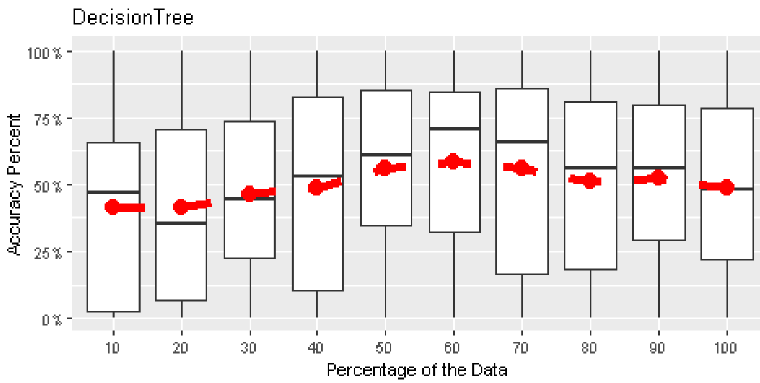


(c) Linear Discriminant Analysis

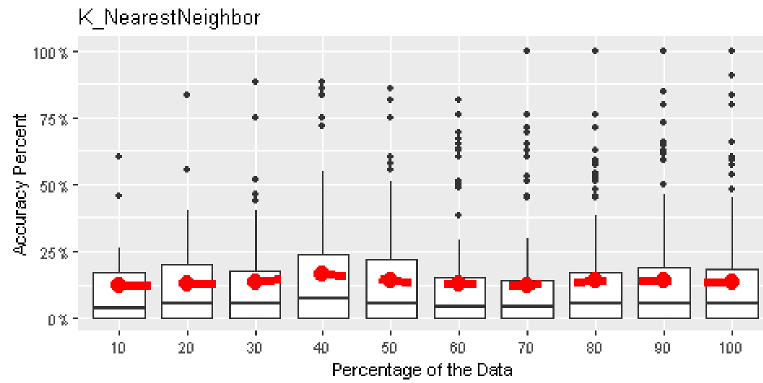


(d) Random Forest

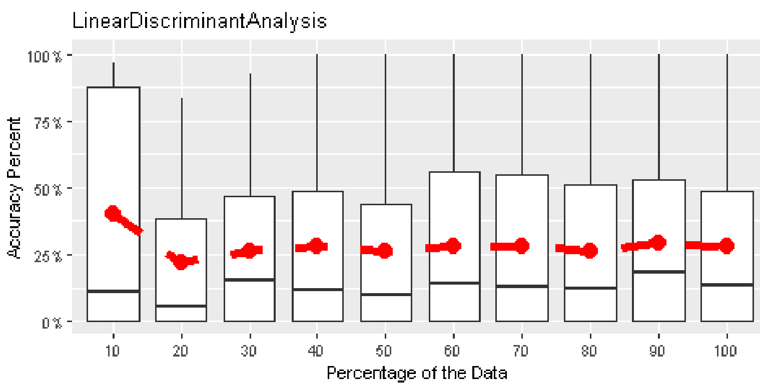
Figure 6.15: Distribution of accuracy obtained from machine learning approaches when data is segmented from Monday to Wednesday for the four different machine learning approaches (a) decision tree, (b) k-nearest neighbor, (c) linear discriminant analysis, and (d) random forest.



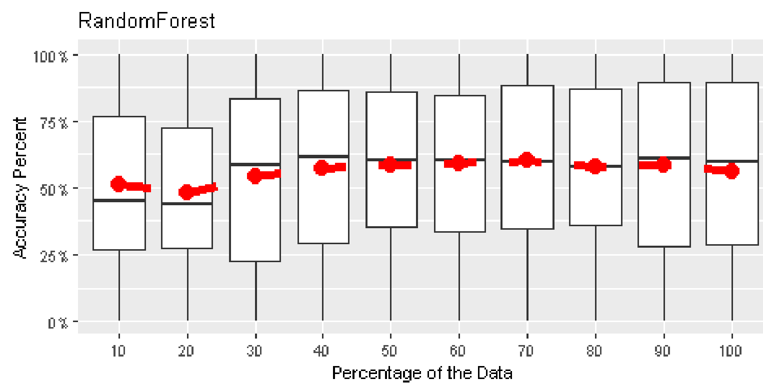
(a) Decision Tree



(b) k-Nearest Neighbor

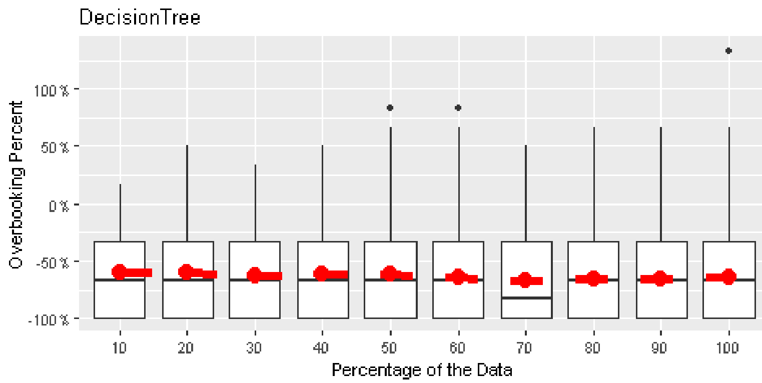


(c) Linear Discriminant Analysis

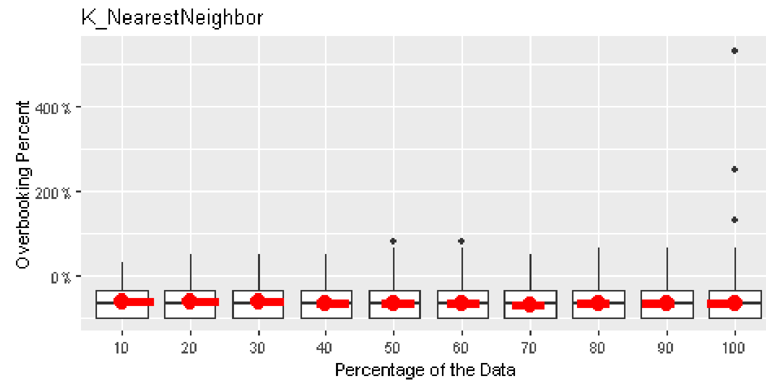


(d) Random Forest

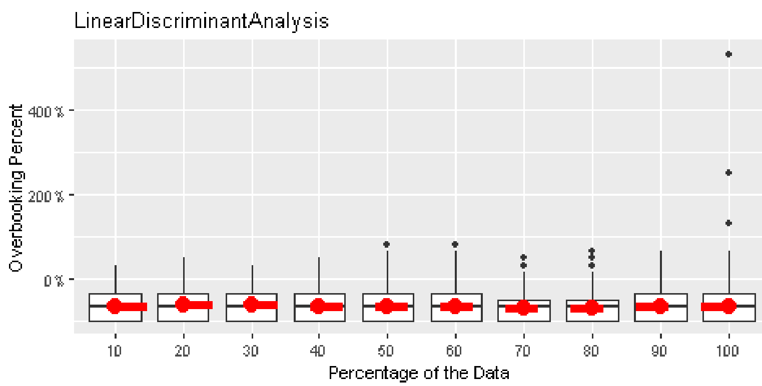
Figure 6.16: Distribution of accuracy obtained from machine learning approaches when data is segmented from Thursday to Friday for the four different machine learning approaches (a) decision tree, (b) k-nearest neighbor, (c) linear discriminant analysis, and (d) random forest.



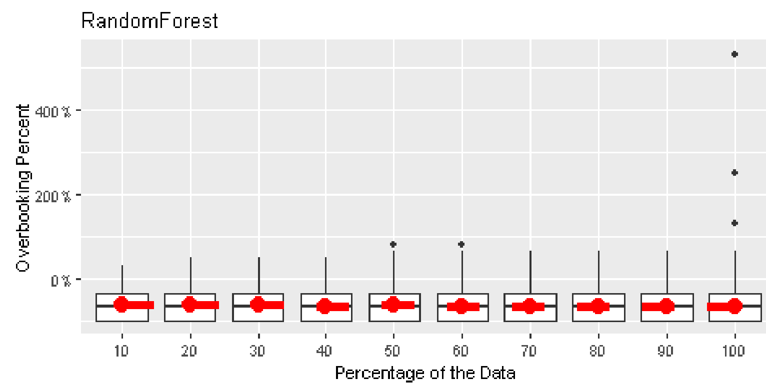
(a) Decision Tree



(b) k-Nearest Neighbor

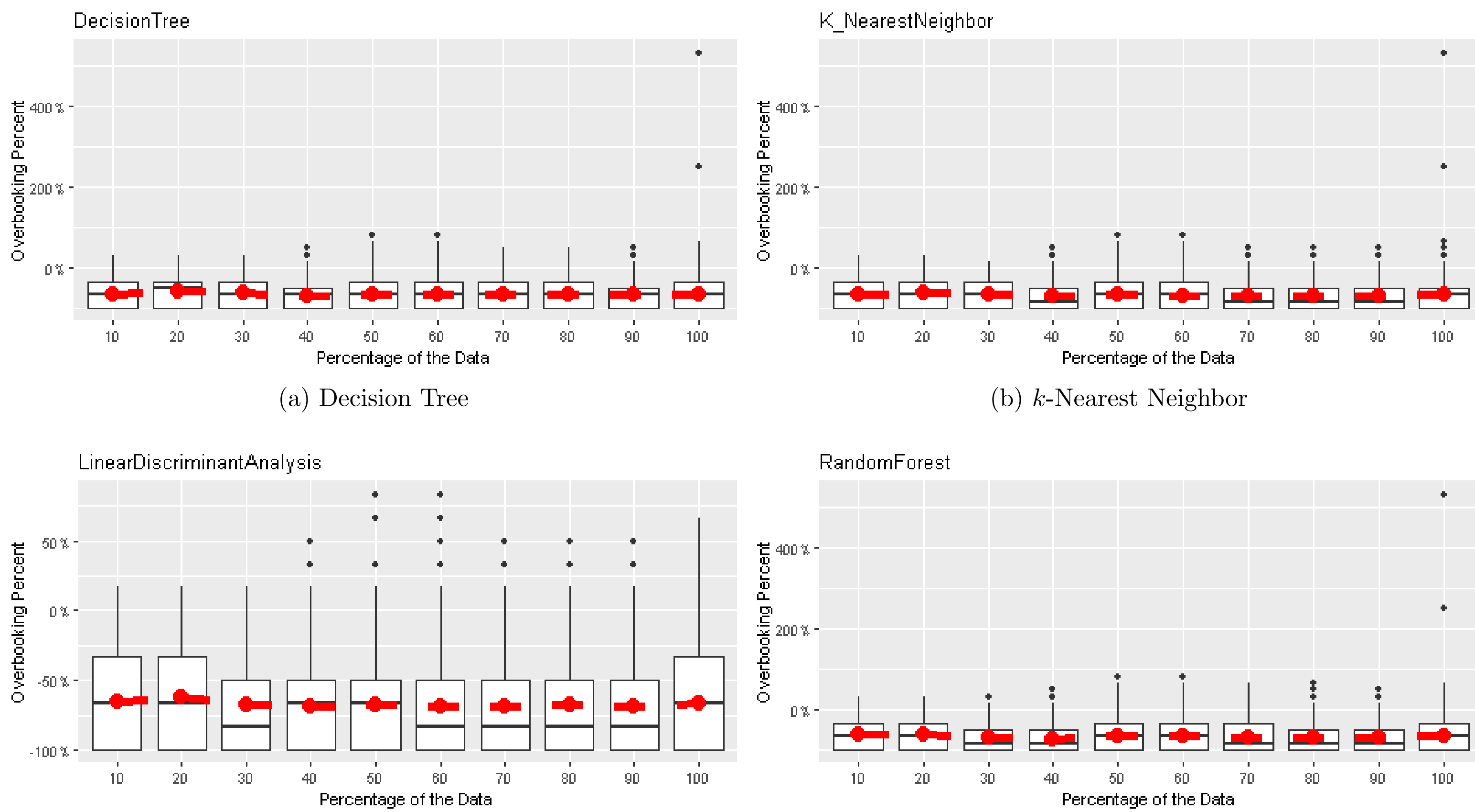


(c) Linear Discriminant Analysis



(d) Random Forest

Figure 6.17: Distribution of overbooking obtained from machine learning approaches when data is segmented from Monday to Friday for the four different machine learning approaches (a) decision tree, (b) k-nearest neighbor, (c) linear discriminant analysis, and (d) random forest.



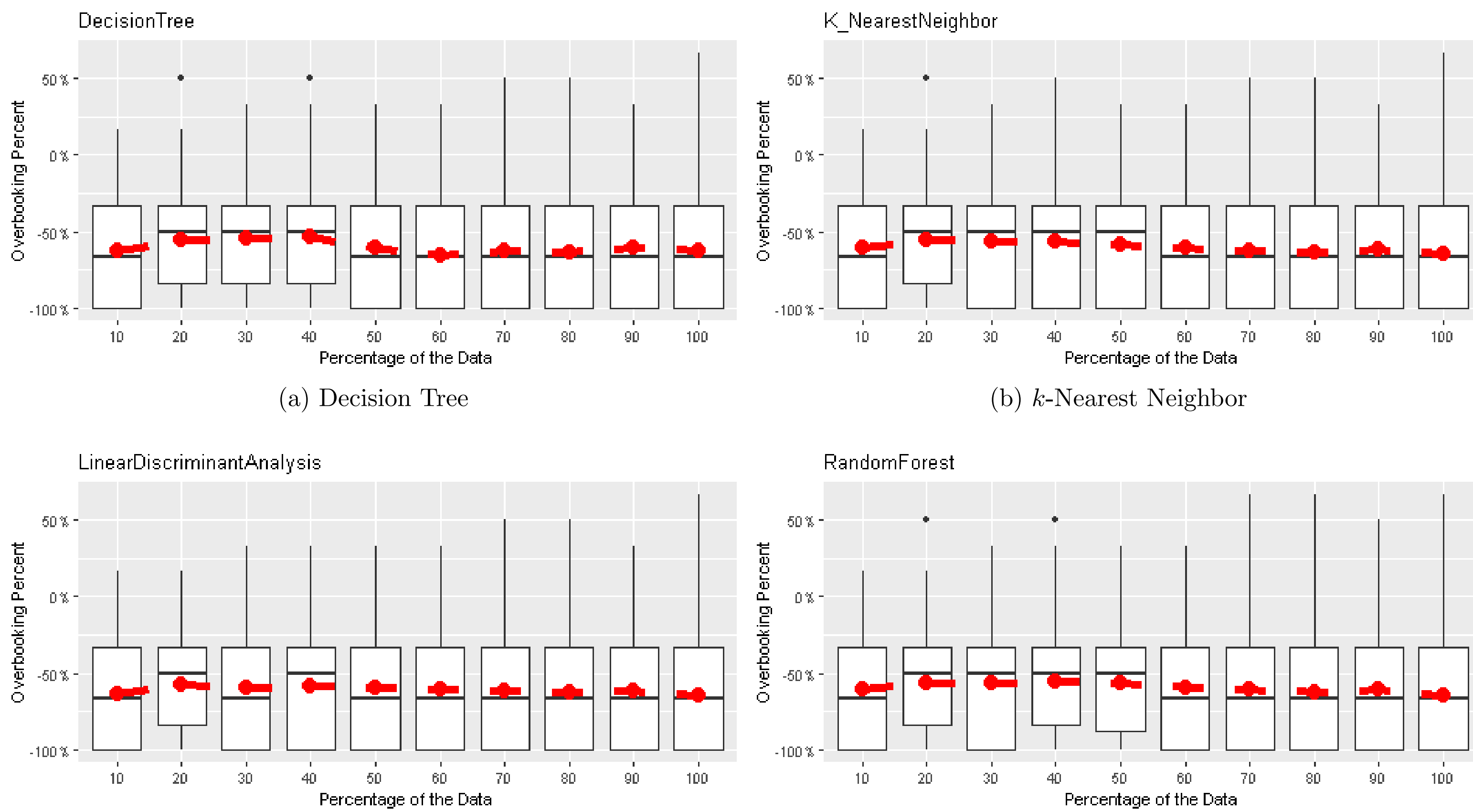
(a) Decision Tree

(b) k-Nearest Neighbor

(c) Linear Discriminant Analysis

(d) Random Forest

Figure 6.18: Distribution of overbooking obtained from machine learning approaches when data is segmented from Monday to Wednesday for the four different machine learning approaches (a) decision tree, (b) k-nearest neighbor, (c) linear discriminant analysis, and (d) random forest.



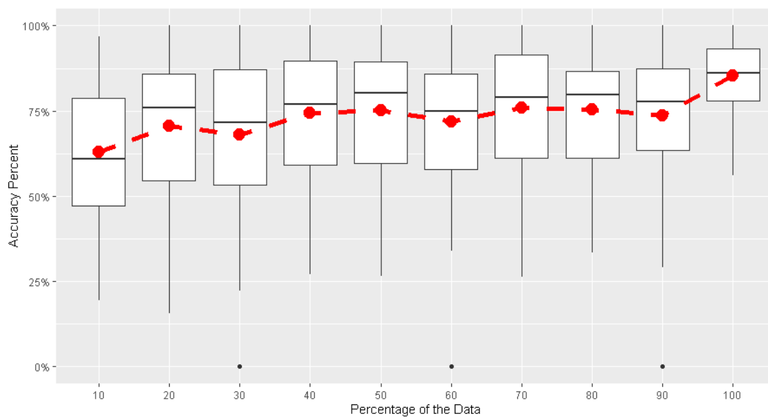
(a) Decision Tree

(b) k-Nearest Neighbor

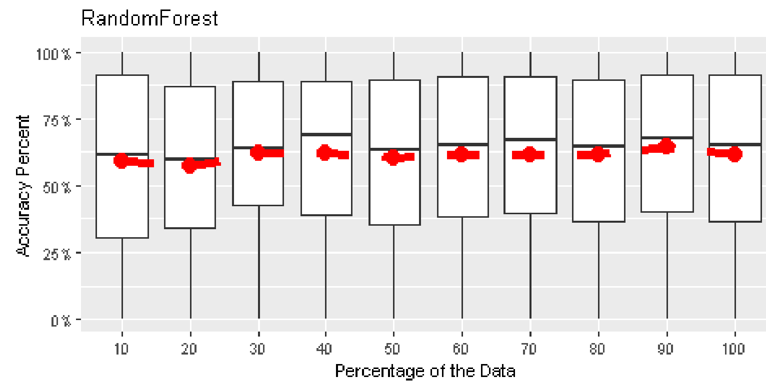
(c) Linear Discriminant Analysis

(d) Random Forest

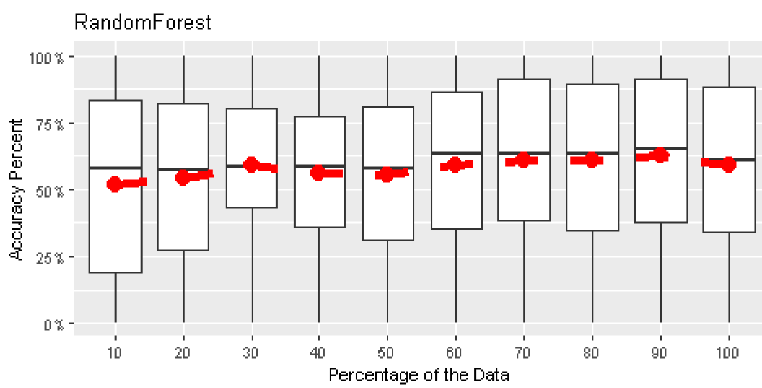
Figure 6.19: Distribution of overbooking obtained from machine learning approaches when data is segmented from Thursday to Friday for the four different machine learning approaches (a) decision tree, (b) k-nearest neighbor, (c) linear discriminant analysis, and (d) random forest.



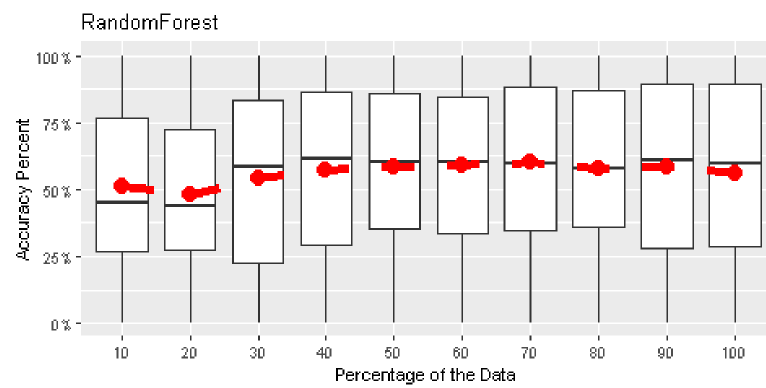
(a) Whole data (includes weekends)



(b) Monday to Friday

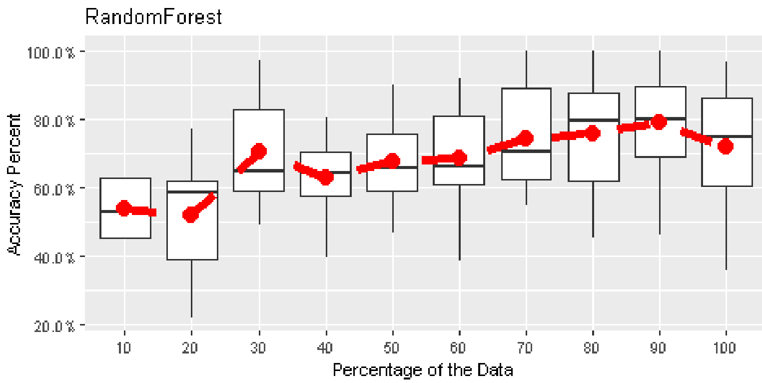


(c) Monday to Wednesday

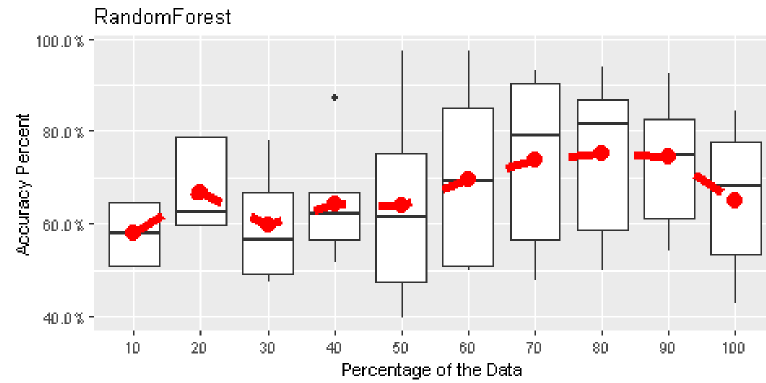


(d) Thursday to Friday

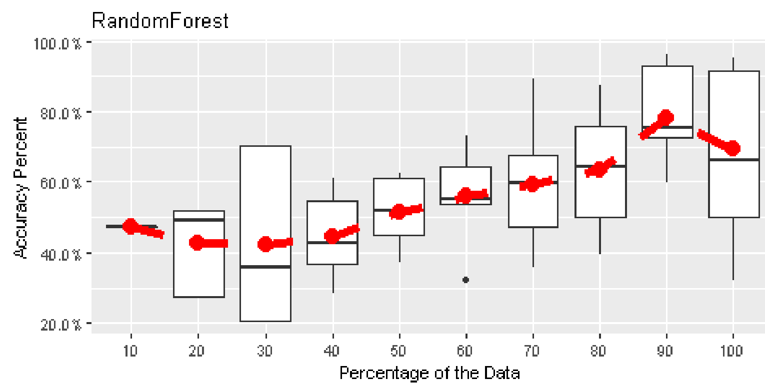
Figure 6.20: Distribution of overbooking obtained from Random Forest approach when data is segmented from (a) Monday to Sunday, (b) Monday to Friday, (c) Monday to Wednesday, and (d) Thursday to Friday.



(a) Monday to Friday

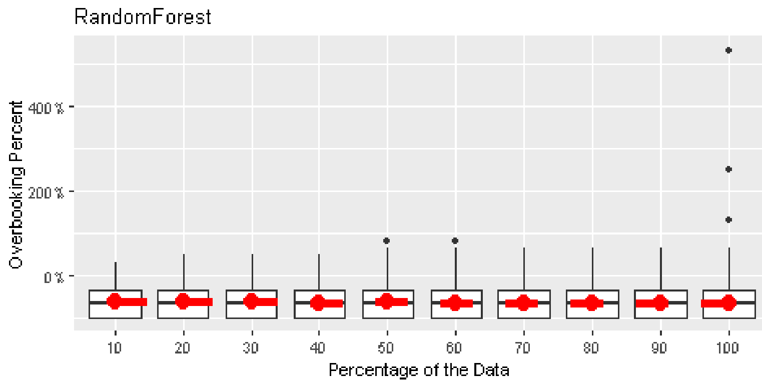


(b) Monday to Wednesday

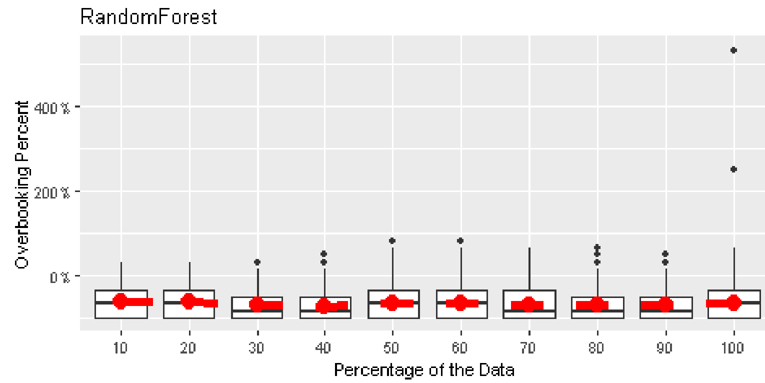


(c) Thursday to Friday

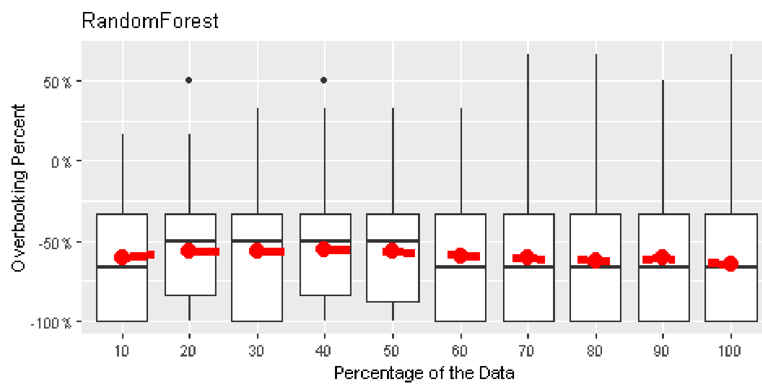
Figure 6.21: Distribution of accuracy obtained from Random Forest approach when data is segmented from (a) Monday to Sunday, (b) Monday to Friday, (c) Monday to Wednesday, and (d) Thursday to Friday.



(a) Monday to Friday

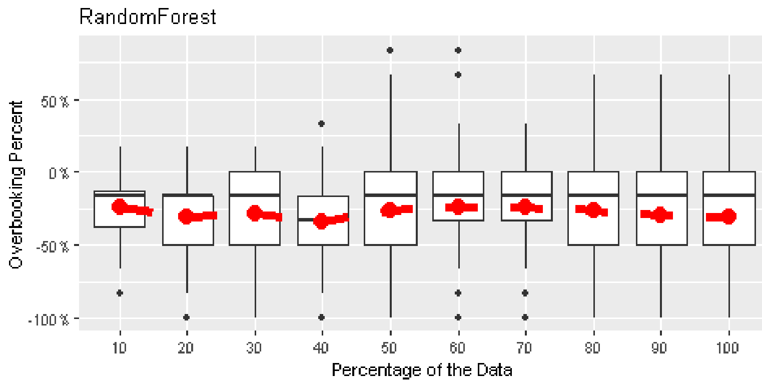


(b) Monday to Wednesday

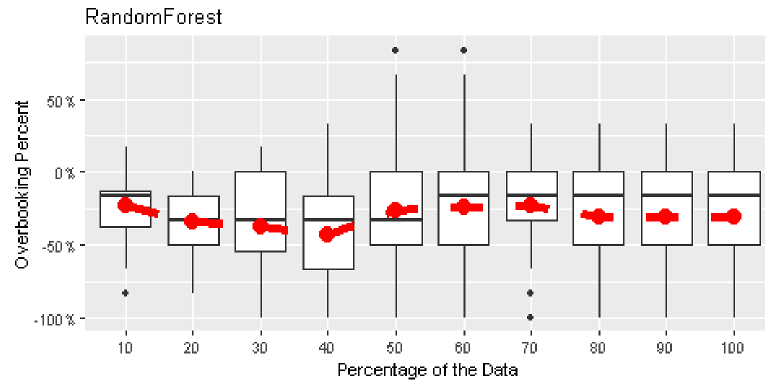


(c) Thursday to Friday

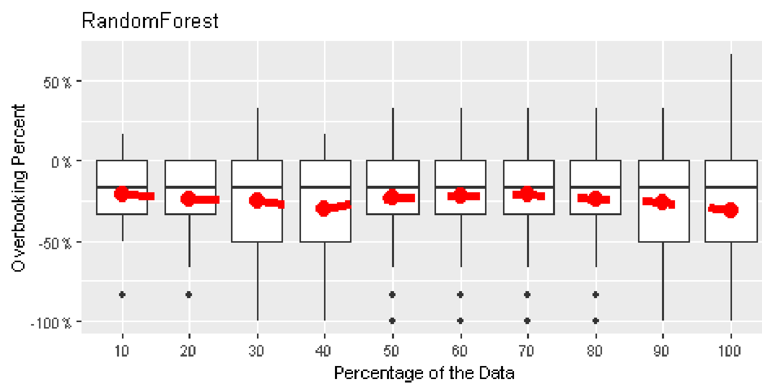
Figure 6.22: Distribution of overbooking obtained from Random Forest approach when data is segmented from (a) Monday to Sunday, (b) Monday to Friday, (c) Monday to Wednesday, and (d) Thursday to Friday.



(a) Monday to Friday



(b) Monday to Wednesday



(c) Thursday to Friday

Figure 6.23: Distribution of overbooking obtained from Random Forest approach when data is segmented from (a) Monday to Sunday, (b) Monday to Friday, (c) Monday to Wednesday, and (d) Thursday to Friday.

Chapter 7

Conclusions

Most concrete dispatch and planning decisions are complex with many dynamic variables therefore modifications of the initial schedule constantly happened and continuously must be planned and re-planned in short periods of time. The efficiency of the proposed solutions depends highly on the knowledge and skill of the planners and dispatchers who, with their experience and knowledge, decide among possible alternatives the efficient use of the company's critical resources such as plants, trucks and vehicles operators. The information to be used by experts is limited since they do not have the discernability of key points such as the visibility of the demand coverage and the costs of the different supply options. The use and enablement of a support tool for strategic and operational decision-making which suggests better alternatives in the allocation of critical resources is necessary to aim lower operational costs and improve client service experience.

In the concrete industry, additions of concrete are as common as cancellations and are equally unpredictable. This provokes in the concrete industry, that schedules needs to re-generated every five minutes due to the magnitude of the changes. Another unique dimension to this problem is the extreme perishability of the product. Most perishable items have a shelf life measured in days, whereas concrete has a shelf life of 2-3 hours. Also, concrete customer's ability to forecast their immediate needs is far less predictable than may be encountered in other industries.

Considering the previous characteristics of the problem, a decision support system is proposed to solve a real-time scheduling problem with perishable products in a time-dependent under a dynamic environment. On a good day, around 90% of the orders change and traffic is fairly predictable. On a bad day, 100% of the orders change, equipment breakdowns occur, and traffic patterns are significantly beyond the expected range. Therefore, system dynamics is a powerful tool to analyze and solve problems with nature dynamic. The development and implementation of this tool has allowed to solve problems of large size in the industrial area of concrete. With the integration of a set of tools, from the graphical interface such as optimization, heuristic and simulation models, as well as the participation of multidisciplinary groups have favored the abstraction of the system in something that can be treated in a better way.

7.1 Contributions

The investigation begins by observing that the existing proposed solutions, which use optimization engines based on mathematical models, perform acceptably when the demand for concrete is equal to or less than 85% of the installed capacity, but their efficiency is markedly decreased when the demand exceeds 85%. In this case, model recommendations are often unreasonable for operation and therefore are not accepted by planners. The objective of the research is to understand the causes of the limitations of the mathematical models and propose alternative solutions that consider the greatest number of elements in the production and dispatch of concrete. Therefore, the use of the tool is intended to improve customer service and company.

Decisions of the tool include the equality of plant usage in the company (balance of services) considering which services should be delivered by certain plants and continue deliver from a specific plant to a costumer that initiates its service from that plant. Also, improve allocation of customer services and trucks. In addition we present the most important contributions of the thesis:

- An original decision support engine for attend the ready-mixed concrete delivery problem was proposed.
- To our knowledge, the presented engine implemented via i-Think is the best technological platform for operational planning under the complexity of the ready mix concrete fulfillment conditions.
- The engine include an optimization of truck balance an truck location in order to fulfill the demand of an international concrete company.
- The engine is consistent and robust in day-on-day operations as the users in the local region and internationally
- The engine provide hourly basis ahead visibility to the dispatchers by using the design concepts, engineering knowledge, and visual aid to represent the operative reality of the ready-mix concrete in order.
- Reduction of the truck cycle time in an average of 5 minutes. This can saves up to 750 000 in annual savings as mentioned in Durbin [7].
- Gives a *best practice* to the concrete company. This is mentioned by directors of the concrete company as they are sufficiently convinced of the importance of this research and its application throughout the concrete industry.

7.2 Discussion

The use of the proposed engine is intended to improve customer service and the company. Engine decisions include equal use of the plant in the company (balance of services) taking into account account what services must be delivered by certain plants and continue delivering a specific plant to a client that starts its service from that plant. Also, improve the allocation of customer services and trucks. Finally, we were able to improve customer service time.

Transition from truck-based dispatching to demand dispatching can have a significant impact on the efficiency of companies in the concrete industry. This transition will not be successfully achieved without the support of the dispatchers. By introducing penalties and bonuses into the model, dispatchers have the ability to fine-tune the recommendations generated by the decision-support tool to more closely mimic their own actions. This has created an environment where trucks are dispatched in an intelligent, responsive fashion that results in a complex, intertwined movement of the trucks throughout the day.

The opinion rendered by the dispatchers is one of the most significant assessments of this decision-support engine. The dispatchers express interest on whats behind the tools they are using. This triggered discussions with the dispatchers to understand some relevant information of the engine. Also, this permit to us the continuous improve of the engine so it can be customized to more closely model how they would dispatch. The more the model is used, the more information we learn to understand the behaviour of decision making of the dispatchers. The explanation of alternative strategies to the dispatchers has also improved. The dispatchers struggle at the beginning to understand the recommendations suggested by the tool but as they understand the recommendation, the engine is more likely to be accepted by the dispatchers and the company. As the dispatchers trust the model more, they allow it to help them during challenging times of the day. The more the dispatchers trust the recommendation, the more willing they are to allow more complex changes (e.g., dispatching trucks from farther plants) in their normal day.

Our solution has been proven in operation satisfactorily in the last two years and has two main elements that allow efficient decision support. The first element is that instead of using an optimization engine based on exact mathematical models, it is proposed to use a simulation optimization engine based on agents which allows in a natural way to incorporate practically any business rule and operational restrictions, having the answer in few seconds. The second element is to have a platform equivalent to an ecosystem that allows real-time business input data to be assembled in seconds. The tool allows planners and dispatchers to validate the input and establish the real time operational constrains via graphic and geographic visualization to the different optimization engines and likewise present the suggestions of the model graphically and geographically generating the confidence necessary to approve and capitalize on the suggested benefits. Other important factor to considered is the maintenance cost for the agent base simulation, in terms of hardware capacity, represents at least 1/3 of the operational cost.

7.3 Future Work

Due to the immense successes of the project, development of the decision-support engine described in this document will continue. The international concrete company, with its parent company in Mexico, is interested into deploy this application throughout the corporation worldwide. We initially propose that each region of the expiation have its own access to the engine as the characteristics of each region variate and changes to the engine need to be performed.

Additionally, there are some areas of research that will be pursued in the future:

- Ensure the consistency across the whole engine from visualization and optimization.
- Deal with real-time issues associated with cyclical re-solving.
- Evaluating alternatives for joint operation when sister companies overlap geographically.
- Change the model to allow different types of trucks to be considered.

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