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A SIMULATION MODEL TO DETERMINE STAFFING STRATEGY AND WAREHOUSE CAPACITY FOR A LOCAL DISTRIBUTION CENTER

Rodrigo De la Fuente
Juan Gatica

Department of Industrial Engineering
Universidad de Concepción
Victor Lamas 1290
Concepción, 4030000, CHILE

Raymond L. Smith III

College of Engineering and Technology
East Carolina University
E. 5th Street
Greenville, North Carolina, 27858, USA

ABSTRACT

Capacity and workforce management in a distribution center can have significant impacts on the overall supply chain. This paper examines the effects of workforce staffing strategies employed in the warehouse operations of a beverage distribution center located in the Bio-Bio Region, Chile. The workforce is responsible for unloading and storing inbound product shipments from distant production plants, as well as retrieving and preparing outbound product shipments for local delivery. A simulation model was used to guide how to improve warehouse operations as measured by load preparation time, workforce staffing costs, and maximum storage capacity utilization. The results recommend increasing warehouse pallet storage capacity to improve efficiency. Additionally, scenarios were evaluated concerning the firm's willingness-to-pay for improvements related to workforce staffing and training. The results indicate that investing in the workforce will reduce the firm's load preparation time by as much as 15%.

1 INTRODUCTION

Supply chain management and analysis is a widely studied topic in the current literature, mainly due to the dynamic environment and the complexities imposed by clients and product features. Within the supply chain, warehousing and distribution operations play a vital role in the delivery of products to customers, but they also add complexity to the system. Improvement in these complex environments often requires advanced methods, such as simulation modeling, to identify optimal capacity, policies, or strategies. Distribution centers (DC) provide an essential role in the supply chain by linking production plants to the distribution network. Daily DC operations encounter problems involving inventory and storage, which, when adequately managed, generate added value to the processes and reduce response times (De Koster et al. 2007).

This study examines a paramount conflict between warehouse operations and human resource management. The conflict originates from current labor regulations imposed by the Chilean government which specifies that workers must be hired with an unlimited duration employment contract upon the renewal of a fixed duration employment contract, which is set at one year. As a result, firms commonly choose to dismiss staff members in the eleventh month of their contract to avoid having to adopt the indefinite contract and cost commitment. Consequently, dismissal of an experienced worker and training of a new replacement worker has negative impacts on cost and productivity. Approaching the matter more strategically, management should consider how many workers should retain the full-time permanent employment contract to achieve and maintain productivity standards. This study seeks to assist management in determining the number of employees that should be kept and the appropriate facility capacity size to improve warehouse operations in the local distribution center. To complete this study, simulation experiments were performed using a discrete-event simulation model developed with Simio simulation software.

2 BACKGROUND

Warehouse facilities can perform several different functions within a supply chain network. As a result, several different classification schemes can be found in the literature. According to Ghiani et al. (2004), warehouse facilities should be simply grouped either as distribution centers or as production warehouses. By comparison, Frazelle (2001) classifies warehouse facilities with respect to their function in the supply chain network, such as the allocation of raw materials, products in process, finished products, distribution, fulfillment, direct local warehouses for customer demand, and value-added service. Another perspective considers the processes of a warehouse which can be classified into one of three groups: (1) load processes, (2) service or storage processes, and (3) exit processes, which mainly include the dispatch function. Liong and Loo (2009), for example, investigated the loading and unloading processes in warehouse facilities by conducting simulation experiments under various scenarios to quantify worker utilization and waiting time delay. These results were used to identify bottlenecks and to develop improvements in the system. One recommendation included increasing the manual labor capacity to reduce the excessive use of overtime and the waiting time delay experienced by clients.

Understanding the arrival process for a warehouse facility is important in the development of a simulation model, especially since it strongly influences storage capacity dynamics in warehouse operations. According to Nelson (2013), a non-stationary Poisson process is widely used in practice to model arrival processes that vary throughout time; and, by not accounting for these the results for key measurements can be severely affected. In contrast, Gerhardt and Nelson (2009) demonstrate that the interarrival times of real-world processes tend to depart from Poissoneness by having a much greater, or smaller, coefficient of variation. Such a case is described by Brown et al. (2005) where operations were analyzed for a small banking call center over a period of one year. Using queuing theory analysis, the service process was divided into three fundamental components: (1) client arrivals, (2) client patience, and (3) service duration. Statistical tests were performed for each component to evaluate behavior. The arrival process was then further evaluated to determine whether it was a non-homogenous Poisson process. This was performed by transforming the data into a sequence of random variables, independent and identically distributed (i.i.d.), uniformly between [0,1], which was then evaluated using the Kolmogorov-Smirnov (K-S) test. A logarithmic transformation was then performed to evaluate whether the process was considered a Non-Homogeneous Poisson Process (NHPP). These procedures condition what might otherwise have been considered ill-behaved data for the purpose of reliably modeling an arrival process.

Finally, the methodologies used to determine the size of the warehouse storage capacity, which are a function of inventory policy (Ghiani et al. 2004), must be carefully considered in the development of a simulation model. In the case where products are assigned fixed storage positions, the total space required in the warehouse facility is the sum of the maximum inventory for each product within the evaluation period. In the case where products are dynamically, or randomly, assigned storage positions, the total space required in the warehouse facility is simply calculated based on the maximum inventory attained within the evaluation period. Additionally, more advanced mathematical methods for approximating maximum storage capacity have been proposed in the literature. For example, Karakis et al. (2015) proposed a non-linear model based on the input parameters of the storage capacity and using the known machinery technical specifications and product sizes to determine the dimensions of a warehouse facility.

3 PROPOSED FRAMEWORK

3.1 Process Description

Figure 1 illustrates the relationship between the production plant, distribution center, and distribution route, resulting in the delivery to the client. The process starts with the various supplying plants scheduling production according to a monthly forecast. Once produced, the output is dispatched by truck to the distribution center where the product will be unloaded, placed into stock, later retrieved for the load preparation process, and placed on a local delivery truck. Once dispatched, a truck will leave the distribution center traveling to the customer destinations along a planned route. Supplying production plants manage

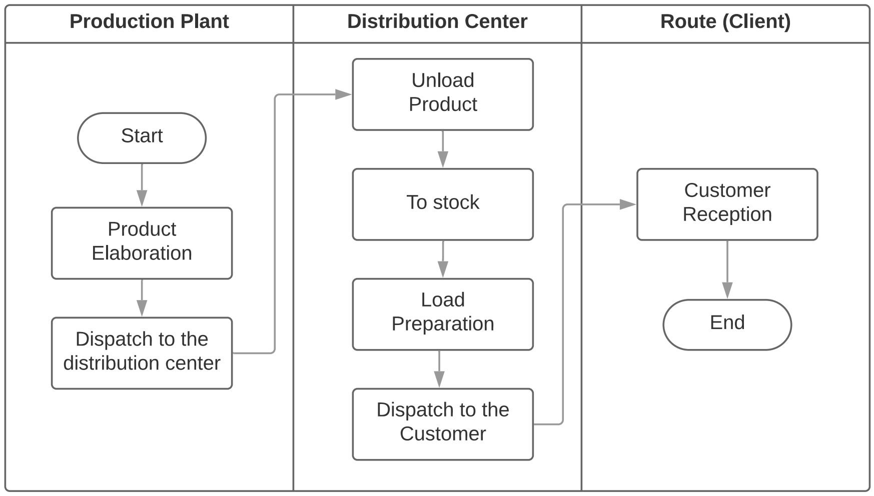

Figure 1: Major steps in the supply chain.

a wide array of products, including bottle containers of different materials, which are uniquely identified using a total of 324 stock keeping units (SKUs). This variety contributes to the complexity in warehouse operations since both the container material and expiration dates must be considered. Additionally, warehouse operations restrict the maximum stacking height due to product packaging integrity concerns, which imposes a constraint on the storage capacity. At the same time, company policy stipulates that products dispatched to customers must be more than 30 days away from expiration. To avoid shortages that would result in sale losses, sufficient stock must be kept on-hand at the warehouse to cover not only the customer demand but also to replace the discovered aged product that cannot be dispatched to customers.

Due to a large number of SKU's it is beneficial to establish product families where products are grouped according to their characteristics. This improves the computational performance of the simulation model and abstracts the complexity of the problem. Groupings were developed based on characteristics that provide interesting qualities relevant to the modeling of operations. For example: the supplier's information can be used to determine the behavior of products arriving at the warehouse; the container material provides information on the capacity needed to store each SKU; the quantity of product per pallet (information used to calculate stocks); and, the flavor of the product allows representing the intention of customers demand. Thus, families are grouped according to the supplier, container material, container size, and product flavor. Using this grouping approach resulted in a total of 61 families, where six of them were multi-pack products.

Product stock levels fluctuate for numerous reasons. Factors observed to contribute to overall stock level fluctuation include supply (50% of activity), demand (41%), dispatch (6%), multi-pack (2%), and miscellaneous ($< 1\%$). In general, increases in stock levels are largely influenced by increased supply; whereas, decreases in stock levels are largely influenced by outflows to customers and the building of multi-pack products. Parameterization of these operations is discussed in the subsections that follow.

Warehouse staff members who perform the product retrieval and load preparation are employed using one of three types of contracts: (1) full-time permanent employment, (2) fixed-term employment, and (3) a casual work arrangement. Contracts for a full-time permanent job are the most expensive to maintain since they require pension contribution, health care, salary, and overtime payment. The last two arrangements are restricted by government regulation not to exceed eleven months in duration.

Productivity during the shift hours is calculated as the sum of the individual productivities, which depends directly on the levels of expertise and fatigue of each worker. The level of knowledge of each worker is determined by the time they work in the company; whereas, the level of fatigue is determined based on the number of consecutive night shifts worked. Contract duration is an essential factor to consider in the study since productivity for product retrieval, and load preparation is directly related to the turnover of personnel. With higher turnover, more fixed-term employment contract workers will be dismissed and replaced with inexperienced staff that requires a learning period before becoming fully productive.

3.2 Modeling Parameters

As discussed by He et al. (2016), the arrival Poisson process must follow these conditions: $N(0) = 0$, independent arrivals, the interarrival times must be adjusted to an exponential distribution, and the number of events in a range of length t is distributed Poisson with average $\lambda \cdot t$ for all $s,t \geq 0$ ($P\{N(t+s) - N(s) = n\} = e^{-\lambda t}(\lambda t)^n / n!$), which also indicates that a Poisson process has stationary increments with $E[N(t)] = \lambda t$. Therefore, in this investigation, arrivals were considered independent among providers since they supply to different families, and a procedure to determine the *Poissoness* of the arrivals was applied to each provider. Verifying whether the arrival process is Poisson, the methodology described by Nelson (2013) was applied, which determines the ratio between the variance of the number of arrivals and its expected number. Thus, the non-stationary Poisson processes that fulfill the ratio should not be significantly different from one. However, the observed values obtained differed significantly. For example, the computed ratio for product originating from the Talca region was determined to be 2.23, indicating a non-stationary Poisson process is inadequate. Additionally, the number of arrivals to the warehouse originating from Talca varies throughout the year; although, there is consistently a significant increase before the Christmas and New Year holidays in December and Chile's Independence Day in September. Furthermore, during the winter season product demand is low historically.

To overcome the departure from *Poissoness*, fluctuations in product shipments arriving at the distribution center were captured in the model using weekly rates. However, inappropriate rounding of the weekly rates decimal values resulted in 74 truck arrivals above what was observed in real-life, which translates into a maximum error of $74 \cdot 30 = 2,220$ overstocking pallets (where the largest quantity loaded by truck is 30 pallets). To obtain a better estimate, we proceeded to represent the decimal numbers of the rates with discrete distributions, in such a way that the expected number of each weekly distribution is equal to the average rate calculated. For example, if the rate is equal to 5.3 arrivals per week, the associated discrete distribution is $Discrete(5; 0.7; 6; 1)$ since $5 \cdot 0.7 + 6 \cdot 0.3 = 5.3$. On the other hand, the mentioned method obtained an average number of arrivals of $2,085.83 \approx 2,086$ in a run of 36 replicas, meaning a deficit of only nine pallets with what was observed and a maximum error of $9 \cdot 30 = 270$ pallets. This last procedure was used to parameterize the number of truck arrivals to the distribution center.

When an inbound truck from the production plant arrives at the distribution center, it is crucial to determine what products and in what proportion they make up the load. To accomplish this, a joint density was created incorporating three critical variables: the truck size, the products contained, and the proportions of truck capacity allocated to each product. In this way, it is possible to determine the probability that a truck arrival has a capacity of 28 pallets, where 40% belongs to family two and 60% to family seven (in this case, the mix is 40-60). Based on the historical data, Table 1 presents the product mixes that occur with the highest frequency. Additionally, to model the products contained in the load a binary vector was used, where each position represents the corresponding family number, with a zero value assigned in case of not including the family and one in the opposite situation.

Next, the combination of the three dimensions of the joint density prepared to model the content of the arriving trucks is presented. In Figure 2 the horizontal axis represents the capacity of the truck, and the vertical axis identifies the thirty most frequent product vectors, which includes the predominance of truck arrivals with a capacity of 30 pallets and first vectors of products, which translates into a higher probability of occurrence. Figure 3, shows the Mix-Vector combination (the third combination, Capacity-Mix, is not shown due to page limit restrictions).

As previously discussed, the outflow of product stock is largely influenced by customer demand. To model this, weekly rates were considered (δ_i), determined by $\delta_j = \sum_{i=1}^{6} d_{ij}/6$ where d_{ij} corresponds to the

Table 1: Proportions of products that make up the loads originating from the Talca region.

Mix Number	Quantity of Products			
	One(%)	Two(%)	Three(%)	Four(%)
1	100	20-80	33-33-33	20-30-30-20
2	-	40-60	25-25-50	30-30-30-10
3	-	60-40	25-50-25	30-20-20-30
4	-	80-20	50-25-25	30-30-20-20
5	-	-	40-40-20	20-30-20-30
6	-	-	40-20-40	30-30-10-30
7	-	-	20-40-40	-

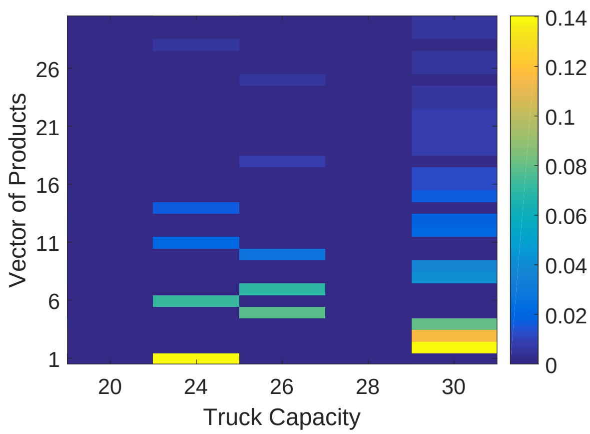

Figure 2: Joint density grouped by Capacity - Vector.

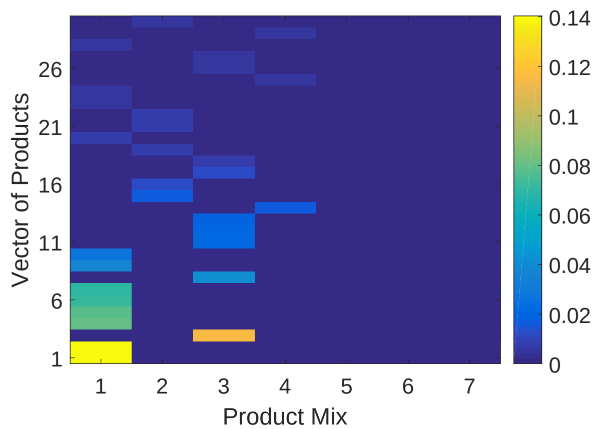

Figure 3: Joint density grouped by Mix - Vector.

demand of week i, with $i \in 1,2,\ldots,52$ representing the week number of the year, and the day j, with j days of the week $j \in 1,2,\ldots,6$.

A similar procedure was performed for the dispatch and multi-packing operations. Given that both occasionally occur within a week, weekly rates were determined based on historical data, and a probability of daily occurrence was defined. Amounts corresponding to "other operations" were adjusted empirically. As mentioned earlier, the productivity of the shift depends on the level of skill and fatigue of each worker. The level of expertise depends on the months the worker has in the company: from 0 to 3 months is considered a beginner level with an expected productivity of 1,500 boxes; from 4 to 6 months average level with an expected productivity of 2,200 boxes; and, greater than 7 months is considered an expert level with an expected productivity level of 2,700 boxes. Variability of staff performance was specified by subject matter experts who set the variability at $\pm$200 boxes, which was modeled using a PERT distribution. For example, workers with an average level the productivity are expressed as PERT(2,000;2,200;2,400). Additionally, a discount percentage was defined for each worker based on the number of consecutive night shifts they had worked. For example, the higher the number of successive nights shifts worked, the higher the percentage of discount on productivity. The discount level for fatigue was considered to be 10%, 20% or 30% depending on whether the worker worked one, two or three consecutive nights, respectively.

A terminology was created to keep track of the staff during the simulation experiments. Contract types were identified as permanent (P), fixed-term (F), or casual work (C). Levels of expertise of the staff were classified as expert level (E), medium (M), or beginner (P). Finally, the shifts were defined by morning shift (M), afternoon (T), or night (N). Infeasible combinations were excluded.

Given corporate regulations prevent storing products outside the warehouse, the maximum utilization of the warehouse was used to determine the storage capacity. For this, it was necessary to monitor the stock level during the simulation period using a Tally type statistic *CapBodegaTally.Maximum*. Then, the capacity of the distribution center for a time t is calculated as $max\ C(t)$, where $C(t)$ is the capacity of the warehouse in time t defined as $C(t) = \sum_{i=1}^{n} S_i(t)/A_i^{max}$. Moreover, $S_i(t)$ the stock of the family i in time t, n is the total number of families, and finally, A_i^{max} is the maximum allowed stack for family i.

3.3 Simulation model construction and validation

The simulation model was constructed using the Simio simulation software platform by following the procedural steps outlined by Law (2008). Supporting data was obtained from the company's SAP enterprise management system for a period of one year, beginning October 2016 through September 2017. Daily product flows are modeled originating from the various production plant suppliers, progressing through distribution center warehouse operations, and completing with product dispatch shipment to customers. Concerning warehouse operations, inbound truck arrivals and product demand dictate the dynamics of product movements. Workforce staffing and storage capacity generally determine the responsiveness and efficiency in completing the required product movements. Figure 4 illustrates the product flow represented in the model, and Table 2 provides a detailed description of the simulation objects. The model considers daily material flows that workers have to handle, such as receiving, packing, and delivery, all influenced by variations on demand. Thus, we model stock levels for each product family daily, to compute warehouse utilization, load time preparations, and as a consequence, labor requirements.

For instance, consider shift $j \in J$ has L workers, and the average productivity level of worker l is defined as NP_l; additionally, worker l's performance is affected by his accumulated workload assigned as $tiredness_l$. Thereby, shift j productivity is given by $PRO_j = \sum_{l=1}^{L} NP_l \cdot (1 - tardiness_l)$. Then, the daily hours required for warehouse operations T can be computed as $T = \sum_{j=1}^{J} \min\{h_j, \frac{Q_j}{PRO_j} \cdot h_j\}$, where Q_j is the total demand to be delivered during shift j, and h_j is the entire time, in hours, available for loading and packing operations during shift j. Each shift can provide the minimum between the total allowed time, and the total allowed time adjusted by overall shift productivity after considering workers tiredness.

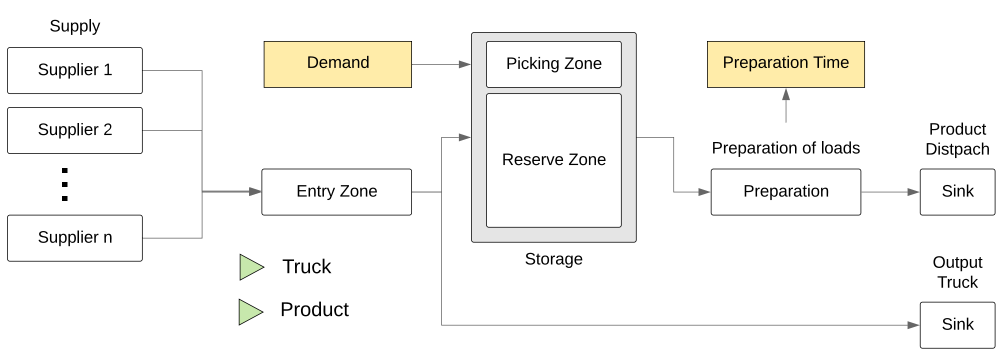

Figure 4: Conceptual diagram of the simulation model.

Figure 5 illustrates the process for the creation of the Product entity type that enters the warehouse operations. The process utilizes a structured loop where entities are created and assigned properties according to the information associated with the inbound truck. When a truck arrives at the distribution center, the product is unloaded and assigned to the picking or reserve area, as appropriate.

Validation of the simulation model was performed by comparing the weekly simulated results of the warehouse capacity with the actual observed weekly results, as shown in Figure 6. Due to the lack of

Table 2: Main structures defined in the simulation model.

Type	Name	Description
Entity	Truck	Generated at the supplier production plant for transporting product to the distribution center warehouse. Possesses information about products being transported.
	Product	Generated in conjunction with a truck arrival to represent a product batch of the same SKU and arrival. Possesses information for product quantity and expiration.
Source	Supplier	Originating supplier production plant generating trucks.
Workstation	Gate	Distribution center location where arriving trucks unload.
	Preparation	Warehouse location used for load preparation.
Storage	Picking Zone	Stores product entities in stock located at the picking area.
	Reserve Zone	Stores product entities in stock located at the reserve area.
Sink	Output	Termination of product entities exiting warehouse.
	Truck Output	Termination of truck entities exiting distribution center.

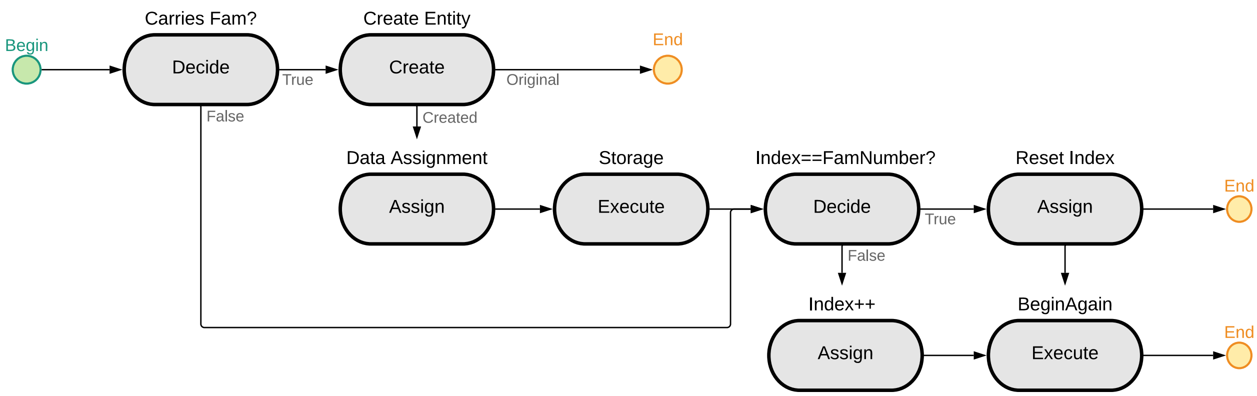

Figure 5: Simulation process for product entry to the warehouse.

historical records, the production time was validated based on expert judgment. Using a Student's t-test to compare the differences between the two unpaired sample averages, the analysis found no statistically significant difference at a confidence level of 95% where equal variances were assumed. Simulated results for the load preparation times averaged 15.11 (0.020) hours, indicating work in the picking area frequently extended well beyond established completion targets. These time overruns result in the delayed start for outbound delivery routes. This result was confirmed to occur in the real system by company administrative personnel. Results from the validation process concluded the simulation model is a sufficient representation of the actual world process which can be used to conduct experiments.

4 EXPERIMENTS AND RESULTS

Experiments were performed using a series of defined scenarios configured in the simulation model to obtain approximations for the load preparation time and maximum warehouse capacity size. Additionally, three demand scenarios, which included pessimistic, expected, and optimistic levels, were used to predict the product demand.

In developing the experiments, it was necessary to define the demand behavior within the evaluation period. To do this, the monthly historical data were analyzed from January 2014 through September 2017, and corresponding to this period forecasts for the monthly sales were made for a time horizon of one year. The best forecasting prediction model was determined based on the Akaike information criterion results. Product demand scenarios were defined as follows: the optimistic scenario was arbitrarily set to be 5%

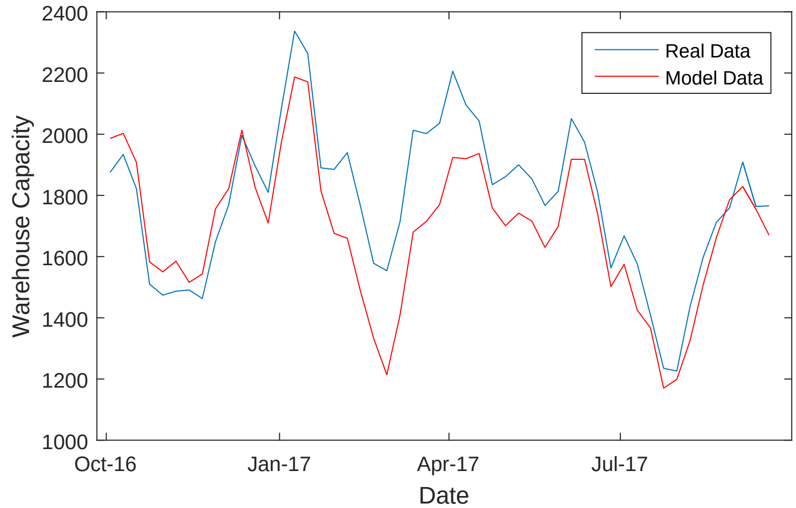

Figure 6: Comparison between the warehouse capacity obtained by simulation model and the real data.

above the forecasted sales, and the pessimistic scenario was arbitrarily set to be 5% below the forecasted sales. This provided a range of demand variability.

Table 3 provides a brief description for each of the experiments. Experiment I is analyzed independently because it specifically addresses the analysis of storage capacity, whereas all other experiments address staffing concerns. Table 4 presents the inputs used in the simulation model for Experiment I. Finally, Table 5 shows the results obtained for the maximum capacity metric used during the simulated period, including the corresponding number of pallets, for each of the demand scenarios. In all scenarios, the required maximum capacity is observed to be lower than the historical data, which is explained by the presence of a negative trend observable in the time series for product demand.

Table 3: Summary of experiments.

Experiment	Description
Experiment I	Determine the maximum capacity required by the warehouse within the simulation period under the three demand scenarios (on average).
Experiment II	Evaluate reductions in staff turnover by valuing service time using scenarios with increased numbers of workers having a "full-time permanent employment contract" type, determined on expected levels of demand.
Experiment III	Evaluate increases in staff turnover by raising the number of workers with a "casual work contract arrangement" type, while maintaining production and expected demand.
Experiment IV	Analyze the situation of layoffs and hiring of personnel, considering different variations between workers having a "full-time permanent employment contract", "fixed-term employment contract" or "casual work contract".
Experiment V	It gathers the scenarios of the previous experiments which results of load preparation times are over the 15-hour goal. The analysis consists of increasing the level of production by 300 boxes per worker, which can be achieved through training, production bonuses or changes in operating procedures that allow an increase in productivity.

The input parameters for each of the scenarios in the remaining experiments and the corresponding results to these experiments are presented in Table 5, where the standard deviation is shown in parentheses. The desired completion time, according to the standards set by the warehouse operations area, is a total time of 15 hours, which will result in the load preparation being finished by 9 a.m., thereby allowing the morning shift enough time to avoid causing delay to distribution operations and to complete cleaning of the

Table 4: Variation inputs simulation model and results for Experiment I.

	Contract (Workers)			Expected Production (Boxes/Workshift)			Demand	Maximum capacity (pallets)
	P	F	C	E	A	B		
Scenario 1	5	5	4	2700	2200	1500	Optimist	2,136.39 (56.72)
Scenario 2	5	5	4	2700	2200	1500	Expected	2,119.72 (52.72)
Scenario 3	5	5	4	2700	2200	1500	Pessimist	2,073.36 (49.21)

warehouse. In general, results show that an investment in staffing increases the overall level of productivity, and consequently, load preparation time decreases.

Table 5: Inputs to the simulation model and summary of results.

Scenario	Contract (Workers)			Expected Production (Boxes/Workshift)			Metrics		
	P	F	C	E	A	B	Average Confection Time (hours)	Staff Cost (USD)	Cost Variation (USD)
Original	5	5	4	2700	2200	1500	16.184(0.034)	150,945	0
II-Scenario 1	6	4	4	2700	2200	1500	15.881(0.033)	154,392	3,447
II-Scenario 2	7	3	4	2700	2200	1500	15.744(0.031)	157,832	6,887
II-Scenario 3	9	2	3	2700	2200	1500	15.399(0.028)	165,797	14,852
II-Scenario 4	11	1	2	2700	2200	1500	14.777(0.028)	173,754	22,809
II-Scenario 5	14	0	0	2700	2200	1500	14.241(0.026)	186,120	35,175
III-Scenario 1	3	5	6	2700	2200	1500	16.697(0.036)	141,919	-9,026
III-Scenario 2	1	5	8	2700	2200	1500	17.368(0.037)	132,887	-18,058
III-Scenario 3	0	4	10	2700	2200	1500	17.692(0.04)	127,304	-23,641
III-Scenario 4	0	0	14	2700	2200	1500	17.625(0.038)	123,028	-27,917
IV-Scenario 1	6	5	4	2700	2200	1700	14.344(0.027)	164,323	13,378
IV-Scenario 2	4	5	4	2700	2200	1700	17.562(0.053)	137,383	-13,562
IV-Scenario 3	5	6	4	2700	2200	1700	14.594(0.027)	160,876	9,931
IV-Scenario 4	5	4	4	2700	2200	1700	17.183(0.051)	140,825	-10,120
IV-Scenario 5	5	5	5	2700	2200	1700	14.586(0.027)	159,807	8,862
IV-Scenario 6	5	5	3	2700	2200	1700	17.037(0.051)	141,893	-9,052
V-T_Original	5	5	4	3000	2500	1800	14.135(0.026)	150,945	0
V-Scenario 1	6	4	4	3000	2500	1800	13.944(0.025)	154,392	3,447
V-Scenario 2	7	3	4	3000	2500	1800	13.907(0.027)	157,832	6,887
V-Scenario 3	9	2	3	3000	2500	1800	13.706(0.053)	165,797	14,852
V-Scenario 4	3	5	6	3000	2500	1800	14.541(0.027)	141,919	-9,026
V-Scenario 5	1	5	8	3000	2500	1800	15.033(0.051)	132,887	-18,058
V-Scenario 6	5	4	4	3000	2500	1800	14.447(0.027)	140,825	-10,120
V-Scenario 7	5	5	3	3000	2500	1800	14.372(0.051)	141,893	-9,052

Experiment V brings together the scenarios found in all previous experiments where the average load preparation time was above the 15-hour target. The analysis consists of increasing the level of productivity to 300 boxes per worker, which can be accomplished through training, production bonuses, or changes in the procedures of operations. These modifications are evaluated to determine if loads can be completed with a duration of fewer than 15 hours.

Results from Experiments II-V are visually summarized in Figure 7. The figure illustrates the impact on average load preparation time in hours as a result of the net annual investment expense allocated toward staffing, which also includes worker training. The current situation is drawn by a black circle in the figure which references the vertical dashed line (red) for the level of annual expense attributed to staff, and the horizontal dashed line (blue) identifies the target time for load preparations set at 15 hours. Also shown in the figure are colored circles representing the experiments, where Experiment II is identified in green, Experiment III in red, Experiment IV in blue, and finally, Experiment V in gray. Additionally, Figure 8 shows the sensitivity of the training parameter in scenarios where the load preparation time was not achieved; workers were subject to additional training to increase their productivity by 300 boxes. Figure 8 illustrates the impact that training and willingness-to-pay will have on the overall preparation time. The vertical difference between circle markers indicates the expected performance improvement over time as new workers gain experience, progressing from 0 to the 300 box goal.

According to Figure 7, all decisions based on the increase of workers with low-cost contracts without increasing staffing (Experiment II in red) present lower costs than the current situation. However, all scenarios are above the blue dashed line indicating that they do not meet the load preparation time goal. On the other hand, the scenarios increasing the "full-time permanent employment contract" workers without increasing staffing (Experiment III in green) imply an improvement in the productivity, but only Scenarios 4 and 5 have a preparation time less than 15 hours although they correspond to the highest investment levels considered in this study.

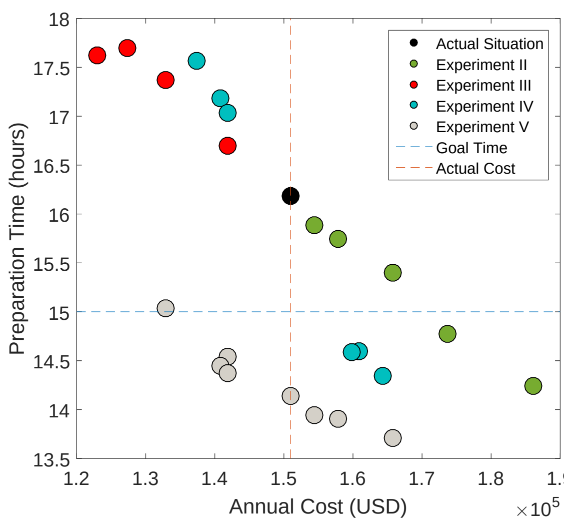

Figure 7: Comparison of results of all experiments.

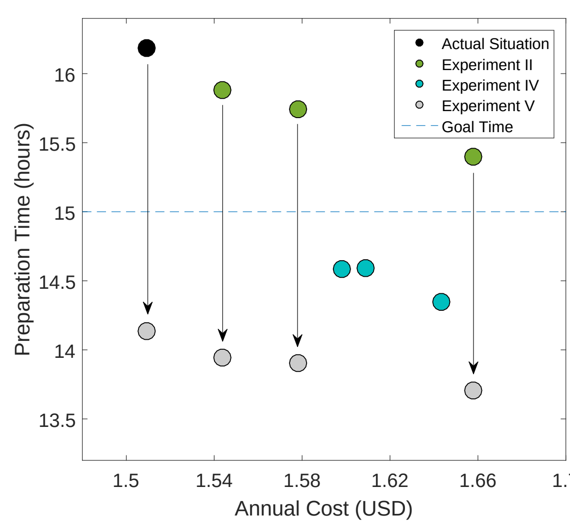

Figure 8: Training sensitivity.

According to decisions related to the hiring and dismissal of workers, it is observed that decreasing the staffing generates results similar to those obtained by the increase of workers with a low-cost contract (Experiment IV in blue). However, increasing staffing produces the best results given it achieves the load preparation time at the lowest cost observed among all the scenarios. While these scenarios are to the right of the dashed red line, they imply an increase in cost.

Finally, the scenarios of productivity increase, through training and/or production incentives, present the best result, since the duration for making loads at acceptable annual cost levels is reached. Depending on the methodology used to achieve an increase in productivity of 300 boxes, there will be an associated cost that results in a shift of the gray circles to the right. For example, Scenario 5 of the training experiment (gray circle with a lower level of investment and close to the target preparation time), has the greatest slack (USD 18,058) to invest in a productivity improvement program, so as not to exceed the annual cost currently spent. Such displacement would place this scenario near the intersection of two dashed lines reaching higher productivity than the current situation at the same cost. It is necessary to consider that these results are based on an expected demand scenario. Thus, in the case of a higher expected level of demand, Scenario 5 would not meet production standards due to the lack of slack concerning the goal of preparation time (blue dashed line). Therefore, scenarios with productivity programs that consider both dismissals of "casual work contract" staff and increase of short-term contracts (Experiment V scenarios 4, 6 and 7), have greater resilience to absorb the variability of demand, and in turn, generate a surplus for investments in productivity.

Regarding the storage capacity, Tompkins et al. (2010) mentions that when a warehouse occupies 80% of its capacity, it is a sign that there is a demand for more space. Results show that the maximum capacity used by the products reaches 2,171.7 pallets on average, with 84.27% utilization, for the expected demand scenario. Under an optimistic demand level, the utilization reaches 84.92% and for a pessimistic scenario 82.47%. These results show that the warehouse reaches limits where it requires more space since they exceed 80% capacity. The warehouse capacity should be $2,224.7/0.8 = 2,714.63 \approx 2,715$ pallets. Given only 2,577 pallet locations are available, it is necessary to increase warehouse capacity by 138 pallets. While the estimated results of the warehouse capacity do not exceed 90% of use, currently, the distribution center must occasionally store products outside the warehouse. This can be explained by the loss capacity due to the great variability of the warehouse. For example, if a certain SKU has been pre-assigned capacity for 10 pallets but only 7 are in stock, there is essentially a loss of capacity equivalent to $10-7=3$ pallets in terms of free capacity. Therefore, for a more specific result, the concept of product assignments must be included to capture the variability caused by the restrictions of this type.

5 CONCLUSIONS

This study conducts a quantitative analysis to advise management on the strategy and investment levels required to achieve the established productivity standards for warehouse operations. Central to this study was the establishment of a framework to address the complexities of an arrival process where inbound products are received from several distant production plants using trucks of various size, containing different product mixtures, and differing product proportions. To reduce this complexity, product family groupings were created to represent a large number of products flowing through the warehouse operation. Additionally, three joint densities based on the family groupings were created to efficiently address the arriving inbound truck capacity, product mix, and capacity-mix. These abstractions improved the overall simulation computational performance. Furthermore, the framework design point was beneficial in supporting the procedures described to address the discovered lack of Poissoness in the arrival process. The resulting simulation model was used to perform a series of experiments based on well-defined scenarios to evaluate the effect of facility storage capacity, and workforce staffing strategies have on productivity and cost.

Facility storage capacity was studied using a forecast for product demand, specified at pessimistic, expected, and optimistic levels, and a procedure for warehouse capacity planning. Results of the analysis support expansion of the available warehouse capacity from the existing 2,577 pallet locations to 2,715 pallet locations. At this capacity level, the maximum utilization of the warehouse will be around 80% for the forecasted expected product demand scenario, satisfying the procedure guidelines. While beyond the scope of this study, future work should be performed using the simulation model to rigorously examine the space loss in the storage capacity due to allocation variability.

Strategies for workforce staffing were studied using the simulation model to perform a series of experiments. In general, results show that dismissal of a worker, for any employment contract type, leads to annual savings up to USD $27,917; however, this decision will worsen the load preparation times with overruns above 2.5 hours. Workforce staffing scenarios that achieve the 15-hour standard for load preparation were observed to increase annual costs by at least 6%. Additionally, when changes in worker contract types are permitted, such as the transition from "fixed-term employment" or "casual work arrangement" to "full-time permanent employment," personnel turnover declines and load preparation times satisfy the set standard, although at higher costs (USD $22,809). Finally, improved training has a favorable result where load preparation times meet the set standard, and a surplus of up to USD $18,058 is generated.

The company's willingness-to-pay, or make investments, regarding its workforce staffing is a critical consideration in the analysis. If the company's willingness-to-pay is minimal, or zero, the firm's best action will be to dismiss workers under the "fixed-term employment contract" type before renewal and reinvest this savings into a training program that increases worker productivity, where the investment does not exceed USD $10,120 per year. As a result, high personnel turnover will occur, and ongoing worker training will be needed to improve worker productivity to achieve the load preparation time standard.

By comparison, if the company has a willingness-to-pay regarding its workforce staffing then one of the three alternatives is recommended: (1) hire an additional worker under a "casual work arrangement contract" at an annual cost up to USD $8,862, which will result in the average load preparation time reduced to 14.586 hours; (2) develop a training program to improve productivity at a maximum annual investment up to USD $8,862, which will result in the average load preparation time reduced to 14.135 hours; or (3) permit the change in contract type from "fixed-term employment" to "full-time permanent employment", combined with alternative 2, at a maximum annual investment up to USD $5,415, which will result in the average load preparation time reduced to 13.944 hours. As a result, with a willingness-to-pay for workforce staffing and training will significantly improve the warehouse productivity.

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AUTHOR BIOGRAPHIES

RODRIGO DE LA FUENTE is an Assistant Professor in the Department of Industrial Engineering at the University of Concepción (Chile). He holds a Ph.D. in Industrial and Systems Engineering from North Carolina State University. His e-mail address is rodelafuente@udec.cl.

JUAN GATICA holds an Industrial Engineering Bachelor degree from Universidad de Concepción, Chile. His email address is juagatica@udec.cl.

RAYMOND L. SMITH III is an Assistant Professor in the Department of Engineering at East Carolina University located in Greenville, North Carolina. He holds a Ph.D. in Industrial and Systems Engineering from North Carolina State University. His e-mail address is smithraym17@ecu.edu.