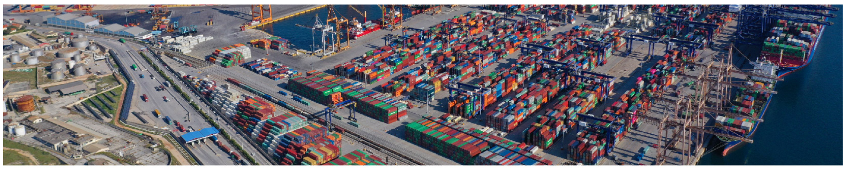

Predictive Demand Modeling for New Services in Hyperconnected Urban Parcel Logistics

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Abstract: *The rapid growth of demand and fierce competition are encouraging logistics service providers towards expanding their competency in terms of offering novel and faster services and reinventing their logistics system so as to profitably and sustainably gain market shares. However, analyzing customer behavior and the underlying causes of demand variability for new services are complex tasks. This paper is dealing with customer behavior modeling for a service provider who wants to extend its offering system to much faster delivery service than ever done before. To adjust its logistic capacities with future demand, it needs to estimate the volume and geographical distribution of demand for new offered services. By capturing customers' sensitivities to the delivery-time observed in historical sales data and geo-categorization of orders in different time factors, a scenario-based demand generation methodology and tool are introduced for generating a wide range of demand scenarios with probabilistic patterns for customer behavior over all service offers with dynamic pricing. These are used to feed a simulator which models large-scale urban logistics networks service and offerings. In an application, it enables testing service capability improvements achievable by leveraging Physical Internet aligned transformation in a Chinese megacity.*

Conference Topic(s): *Interconnected freight transport, logistics and supply networks; PI Modelling and Simulation; Systems and technologies for interconnected Logistics (3D printing/ Internet of things/ machine learning/ augmented reality/ big data/ artificial intelligence/ blockchain/ cloud computing, digital twins, collaborative decision making); Last mile & City logistics.*

Keywords: *Logistics Service Provider; Scenario-Based Demand Analytics; Customer Behavior Modeling; Physical Internet; Delivery-Time Sensitivity; Urban Parcel Logistics; Last-Mile Delivery Network; Hyperconnected Logistics; New Service; Artificial Intelligence.*

1 Introduction

In fast-developing industries with increasing global competition in the introduction of new and innovative services, proper assignment of marketing and operational resources, and best use the available data to explain the demand and sales dynamics of a new service are crucial in success and profitability of new offerings. The research leading to this paper stems from a large-scale collaborative industry-university project (see Campos et al., 2021), notably its work package dealing with demand prediction and customer behavior modeling. The partnering company is a leading Chinese parcel logistic service provider (LSP) that is facing rapid market growth and endeavors to improve efficiency and extend service offers to the less than few hours intra-city delivery services. Such fast delivery is way beyond their current market offers. Therefore, for future demand prediction, it is required to model potential/current customer behaviors and preferences to estimate what portion of current customers may shift to order with new faster services, how many potential customers are to join to consider this company because of its new offers, and how customers are to react if their promised offers are not satisfactorily fulfilled. In this paper, we propose approaches to model customer behavior for new urban parcel logistic services. A key target application of these approaches relates to the comprehensive scenario-based probabilistic modeling of demand and customer behavior for parcel logistics, as introduced by Bahrami-Bidoni & Montreuil (2021). Such modeling notably allows to generate demand to feed the urban parcel logistics simulator developed through the project and to test the simulation performance of alternative logistic systems and offerings, and to monitor the level of customer satisfaction for multiple scenarios (Kaboudvand et al., 2021).

The paper is structured as follows. Section 2 provides a brief literature review. Section 3 focuses on historical demand and behavior data analytics. Section 4 tackles demand and customer behavior modeling for new services. Section 5 introduces a creative methodology inspired by generalized Bass model to analytics of price-based demand response. Section 6 presents a proposed scenario-based user-interactive application and its uses. Finally, section 7 concludes the paper through a synthesis of the contribution, limitations, and avenues for further research.

2 Literature review

The detailed taxonomy illustrated in Figure 1 provides a comprehensive application-oriented overview of the existing literature on demand and customer data analytics. Analytics is known as the scientific process of transforming data into insights for making better decisions, and at a conceptual perspective level, it is commonly divided into four stages (Wang et al., 2018): (1) descriptive data summarization and visualization for exploratory purposes, (2) explanatory diagnostic models that estimate relationships between variables and allow for hypothesis testing, (3) predictive models that enable forecasts of variables of interest and simulation of the effect of marketing control settings, and (4) prescriptive optimization models that are used to determine optimal levels of control variables. Some of the techniques and methodologies adopted or developed to address each application have been summarized in Figure 1. Moreover, Figure 1 shows that the size and degree of structure in data increases from right to left, and the feasibility of the higher level of analysis decreases as a function of big data dimensions. It illustrates that the information value of the data grows as its volume, variety, and velocity increase, but that the decision value derived from analytical methods increases at the expense of increased model complexity and computational cost. Wang et al. (2018) and Chicco G. (2016) in their review papers provided a critical examination of analytics methods, with a marketing focus, by tracing their historical development, examining their applications to structured and unstructured data generated within or external to a firm, and reviewing their potential to support marketing decisions.

The application of smart meter data analytics on customer behavior (Wedel & Kannan (2016)) are particularly revealing in regard to our paper due to its emphasis on customer behavior. As summarized in Hong & Fan (2016), there are three ways to modify the workflow to generate probabilistic forecasts: 1) generating multiple input scenarios to feed to a point forecasting model; 2) applying probabilistic forecasting models, and 3) augmenting point outputs to probabilistic outputs by imposing simulated or modeled residuals or making ensembles of point forecasts. The scenario generation method was also used to develop a probabilistic view of power distribution system reliability indices (Black et al. (2018)).

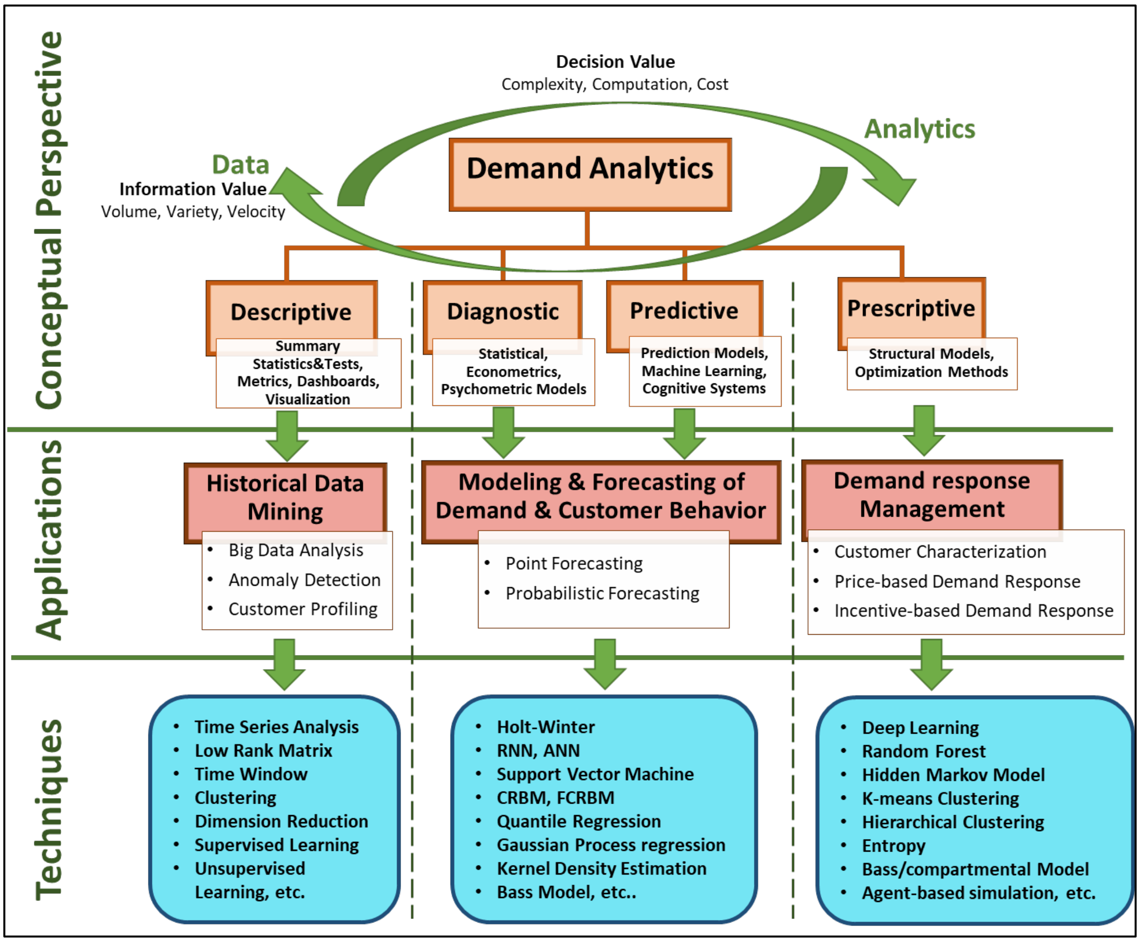

Figure 1: Taxonomy of literature review over predictive demand and customer data analytics

The Bass model was first to forecast demand for new products which have been widely used in new product forecasting mainly because of its concise conceptual framework, parameter setting and good explanatory ability (Bass, 1969). It was defined using a differential equation in which purchases are initiated by mass communication and further driven by word of mouth (WOM) from past purchases. Bass model and its various extensions (e.g. Ramírez-Hassan & Montoya-Blandón, 2020) typically explain the customer purchase process at a highly aggregate level of a market which does not allow for capturing customer heterogeneity. Moreover, they assume that all customers can communicate with all the others (perfect mixing), an assumption often violated in observed network of customers. Consequently, their estimates are highly biased and hard to relate to customer behavior (Abedi, 2019). Bass model and its extensions require the accuracy and completeness of sales data to ensure prediction accuracy, and this type of models is also difficult to adapt to the complex and changeable market environment.

Following the Bass model and its variations to model adoption of a new product, a variety of methods have been proposed: agent-based simulation models (e.g. Rand & Rust, 2011; Kiesling et al., 2012); equation-based models, particularly, compartmental modeling (e.g. Rahmandad & Sterman, 2008; Hariharan et al., 2015). These have in common modeling the adoption pattern at the level of each compartment. Compartmental models add spatial and psychographic segments to Bass-type models, allowing modelers to approximate the heterogeneity, clustering, and communication network of customers, while retaining an analytical structure. These models have been mainly explored in the context of demand forecasting and describing customer behavior, but their suitability as a scalable modeling tool to support large scale marketing and/or operational decision making is not explored.

Abedi (2019) proposed a flexible compartmental model and assessed its suitability in terms of use of data, adherence to micro-level customer behavior, and use in large scale decision making. The paper reveals that compartmental models result in estimates that are less biased and can predict the shape of the adoption curve significantly better than the Bass model. A hybrid new product demand forecasting model proposed by Yin et al. (2020) combines clustering analysis, using a fuzzy clustering-rough set method, and deep learning, using a long short-term memory (LSTM) neural network model. First, they make a primary prediction based on classical Bass model, where fuzzy clustering and rough set methods are used to obtain the attributes of new product through the historical sales data analysis of related products. Then, they correct the prediction error by a LSTM model to form robust predictive results. Temporal sales pattern are often dynamically influenced by word of mouth, previous experience, and loyalty as well as by marketing/advertising and distribution support (Abedi, 2019). Demand estimates for new products in the existing methodologies mostly rely on adoption patterns through customers' network connections and products' similarities. Until now, existing prediction models for new services have rarely been fully validated in terms of quality and consistency. Yet the need for such models is significant in parcel logistic systems, as making such predictions is part of critical tasks faced by LSP managers on a regular basis.

To address this problem, we constructed three connected models hereafter presented. First is a model that predicts total customers who consider the LSP to order (customers who come to the system-centers or website- and receiving offers). This is a scenario-based mathematical model that has been proposed for hourly long-term demand, which consists of a nested combination of three subsections using 2-D representations for modeling specific events and the hourly variation within a week. Second is a model of customer behavior and sensitivities to the delivery time. This model, for any scenario assumption, will determine the probability of selecting among offers by different types of customers. Third is a model providing probabilistic parameter values of the above two models in different scenarios. In our reported research experimentation, the first two models were implemented inside the parcel routing simulator. For the third model, we provided an AI-based App with a user interface to compute the value for input parameters of above two models based on the specific assumed scenario. Then we fed values of these parameters to the comprehensive parcel routing simulation model (in CSV files) and investigated the impact of customer preferences on demand. During simulation runs, we could see how the source and destination of orders is generated in the area and how the customers will select among offers. We also tested the performance of simulated logistic system for that specific scenario. In the rest of paper, four stages of analytics in this study have been presented.

3 Historical data analytics

Predicting demand faces many information challenges. For instance, estimating potential intracity demand for parcel logistics in an overall megacity market depends on a lot of factors such as population and microeconomic growth factors to name a few. Most challenging is the lack of knowledge about potential customers who approach diverse competitors and those who reject all offers. In most cases, the only direct information one can get comes from the historical sales data of one or a few LSPs and is about those customers who approached and ordered from a given LSP. Rarely are logged rejected offers at sale time, nor the fact that the customer considered several LSPs.

3.1 Big data analysis and anomaly detection

The growth of customers in this sector has resulted in the use of big data analytics to understand customers' behavior in predicting the demand of items. It uses a complex process of examining large amount of data to uncover hidden patterns in the information. It is established on the basis of finding correlation between various parameters that are recorded, understanding purchase patterns and applying statistical measures on collected data. For this purpose, a big real-world Chinese megacity database has been studied as a bench test including one-year waybills and Barcode Scanning streaming (in terabytes volume) as well as some multivariate data fusion such as Latitude/longitude geographical information about hubs and customers, Socio-demographic info and so on which all have been used for profiling different type of customers and clustering them in terms of their preferences over services and their sensitivities on delivery-time. Cleaning this big data, detecting anomalies/outliers, and estimating Null/missed data was a challenging part of this project in the first steps.

3.2 Customer profiling

Customers' diversity can be modeled through geo-categorization. For instance, consider a city as a grid of small units such as in Figure 2. These units can for example represent zip codes. Based on the type of buildings, facilities or departments, it is possible to categorize customers who are living in each unit. Grid units can be categorized as entirely or partially be business, industrial, residential, etc. Thus, to model customer behavior we tried to categorize potential and loyal customer's preferences based on their order types and geographical-sociodemographic characteristics and probabilistically modeling their behaviors as presented in section 4.3 to see how they choose among offers (or reject them).

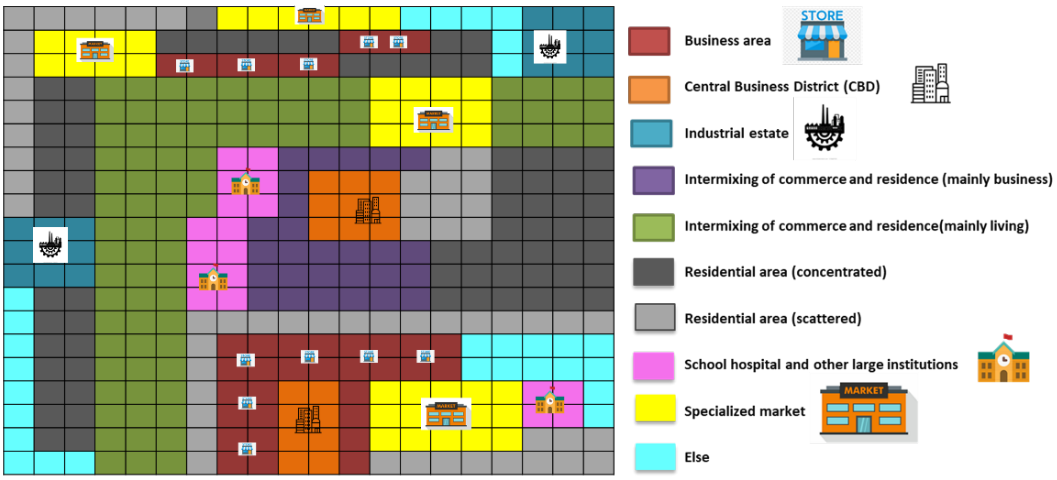

Figure 2: City as a grid of units with the corresponding type of area

4 Modeling demand and customer behavior for new services

4.1 General perspective of proposed framework

The proposed approach for implementing the demand and customer behavior model as well as feeding its outputs to the given simulated logistic system have been summarized in Figure 3. In this project, we have used an urban logistics simulator developed using the Anylogic tool to simulate the parcel routing logistics with offering service levels (Kaboudvand et al. 2021). Probabilistic modeling and analytics, based on multivariate data, customer profiles, and historical sales trend over past time intervals, enables generating probabilistic demand patterns, customer preferences, and price-based demand response patterns into the simulated virtual world which are explained in sections 4.2, 4.3, and 5. This sets the stage for the agents operating the logistic system in the simulator.

Generation of potential orders by the demand generator requires knowing the feasible service types and also estimating their costs to find the feasible domain area for the offers. As an LSP may have some predefined routing cycles in the logistic model, and an estimate of how long will take each trip between different logistics hubs during different times of day, it becomes possible to estimate feasible piecewise trajectory trips, and their duration between source and destination of an order. For doing this, the offering manager collaborates with the logistic model to get a real-time robust estimate on the shipping time of the parcel from pickup point to the delivery point through the system. Based on this information, the LSP is to filter offers by removing those that are infeasible with respect to the fastest possible delivery time. After LSPs provide the set of feasible service offers, the customer chooses between them or reject them all, in a way that can be estimated through the probabilistic model of customer behavior computed by models in section 4.3 and 5. If the customer's preference is not in the list of LSP offers, the customer will choose or not the next best fitting feasible offer, which can be modeled based on cumulative probability function of corresponding order category.

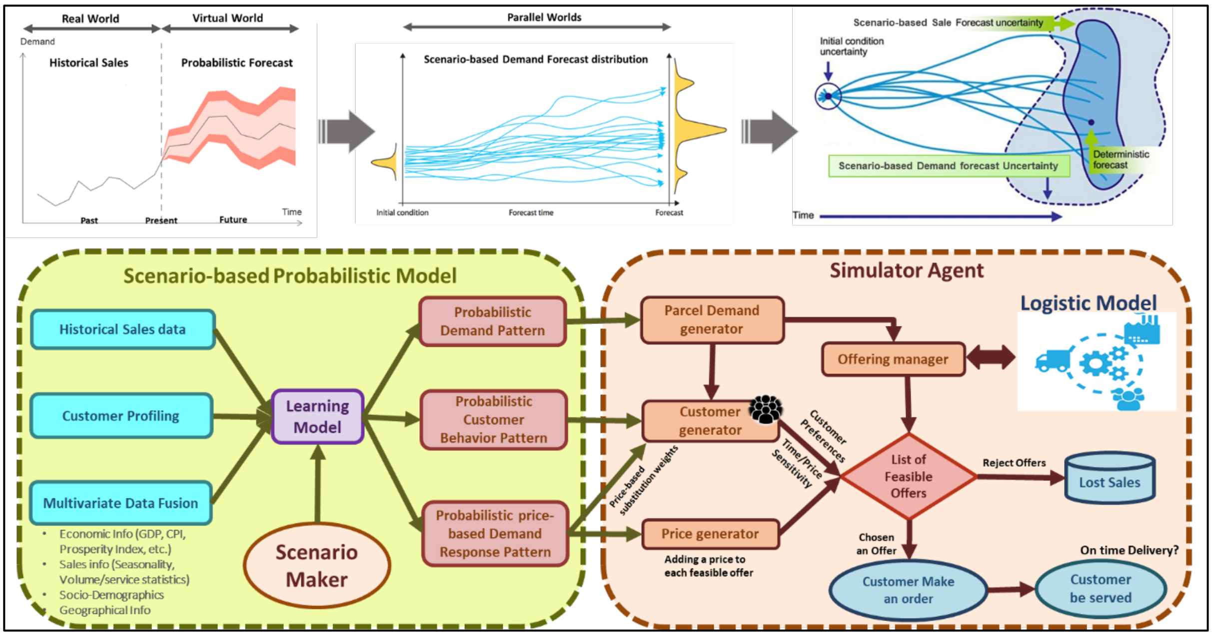

Figure 3: Scenario-based predictive modeling of uncertain demand

After enough simulation iterations over intervals and scenarios, this leads to adequately estimating the distribution of scenario-based forecast for potential demand, sales, and lost sales. The reference Kaboudvand et al. (2021) provides more details regarding how the simulator parameters are obtained from probabilistic customer behavior models as inputs, how they interact with each other, and how verification and validation of the simulator are conducted.

4.2 Modeling probabilistic pattern for scenario-based demand volume and geographical source/destination distribution

To generate the patterns for demand volume, we use a mathematical model inspired by the methodology proposed in Filik et al. (2011) which contains a nested combination of three subsections using weekly residual load variations and two-dimensional representations for modeling specific events and the hourly variations within a week. A data-driven learning and fitting surface functions to this template structure allow us getting the base pattern of demand volume with lower/upper bounds on the probabilistic range at the hourly granularity over a given forecast period. We have introduced and explained this proposed approach with more detail in Bahrami-Bidoni & Montreuil (2021).

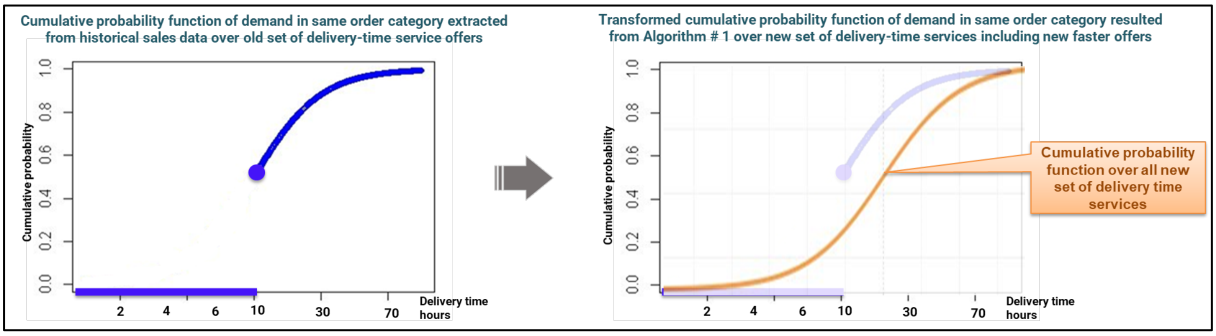

Figure 4: Scenario-based cumulative probability demand estimation for new faster services (example)

D: *Average daily demand forecasted by first model presented in section 4.2.*

P: *Total percentage of potential customers seeking new faster services (one of scenario assumption).*

$O^{Old} = \{t_1^{Old}, t_2^{Old}, \dots, t_s^{Old}\}$ *: The set of all promised delivery-times in the old service offering system.*

$O^{New} = \{t_1^{New}, t_2^{New}, \dots, t_r^{New}\}$ *: The set of all faster delivery-times in the new service offering system.*

$V^c = \left(v_{t_1^{Old}}^c, v_{t_2^{Old}}^c, \dots, v_{t_s^{Old}}^c\right)$, $\sum_{i=1}^{s} v_{t_i^{Old}}^c = 1$ *: Probability vector of demand over the set of old offering services.*

Algorithm #1:

Goal: *Computing continues cumulative probability function of category c for selecting over all delivery-time services.*

Stage 1: *Compute the vectors* $K^c = \left(K_0^c, K_1^c, K_2^c, \dots, K_s^c\right)$,

where $K_0^c = P * D * w_{pd}^c$ *and*

$K_i = (1-P) * D * w_{pd}^c * v_{t_i^{Old}}^c$, $i = 1, \dots, s$

Stage 2: *Normalize* K^c *to get the vector* $K^{c\prime} = \frac{1}{\sum_{i=0}^{s} K_i^c} K^c$

where its first component $K_1^{c\prime}$ *is the cumulative probability of demand over all new offering services.*

Stage 3: $a = K_1^{c\prime} \big/ \left(t_r^{New}\right)^2$, $L = K_1^{c\prime}$

Do for $i = 1:r$
$\hat{F}(t_i^{New}) = a * (t_i^{New})^2$
End

and

Do for $i = 1:s$
$L = L + K_{i+r}^{c\prime}$
$\hat{F}(t_i^{Old}) = L$
End

Stage 4: *Fitting below function inspired by Bass diffusion Model* $F_{p,q}(t) = \left(1 - \exp(-(p+q)t)\right) \big/ \left(1 + (q/p)\exp(-(p+q)t)\right)$ *and compute the optimal* p^*, q^* *coefficients with lower function error to the data sets* $T = \left\{t, \ t \in (O^{New} \cup O^{Old})\right\}$, $\hat{F}(T) = \left\{\hat{F}(t), \ t \in T\right\}$

Return $F_{p^*,q^*}(t)$ *As the cumulative probability function of category c for selecting over all delivery-time services.* $(t \in T = O^{New} \cup O^{Old})$

Figure 5: Algorithm for simulation of customer preference over all potential continuous delivery-time

4.3 Modeling probabilistic customer behavior pattern for demanding services

First, a category based on four attributes (*h, s, r, d*) has been considered for each potential order: *h* is the time window of placing order (which hour of a day), *s* and *r* are category types of sender and receiver of corresponding parcel (type means geo-categorization in section 3.2), and d is the categorical distance variable between order's source and destination (e.g. *d1< 10 km, 10 km<=d2<40 km, 40 km <=d3*). For instance, a potential order category could be a parcel from a business to a residential area with *d2* distance at 2 PM. Moreover, the proportional demand weight for faster services (w_{pd}^c) is computed for order category *c* by $w_{pd}^c = w_{TS}^c * w_{fd,t_1^{old}}^c$, where the delivery-time sensitivity weights (w_{TS}^c) obtained by equation (1).

$$w_{TS}^c = R^c(t_1^{old}) \big/ R^c(t_1^{old}) + R^c(t_2^{old}) \tag{1}$$

where $R^c(t_1^{old})$ and $R^c(t_2^{old})$ are the average demand rates in category *c* for the first and second fastest delivery-time offered on historical sales data, and $w_{fd,t_1^{old}}^c$ is the fractional historical demand volume weight for the t_1^{old} in category *c* among all other categories.

The cumulative probability function over previously available offering set of delivery times will be extracted from historical sales data as a base (e.g. see left diagram of Figure 4). Then, based on assumptions in given scenario and using the algorithm in Figure 5, a new piecewise cumulative probability function will be simulated over all the new sets of delivery time services and finally lead to completing the probabilistic customer behavior model over a new set of service levels for a given scenario (e.g. see right diagram of Figure 4). In the first two steps of algorithm, the cumulative probability demand over all new offers is obtained and demand probability over old offer set calibrate based on value of *P* in scenario assumption and *d* from 4.2). In stage 3, a rough estimate for *F(t)* over new delivery-time services is computed and then the optimal value of *p* and *q* parameters will be obtained such that continues Bass model function fitted to the estimated discrete cumulative probability in corresponding order category.

5 Price/Incentive-based probabilistic demand response analytics

Research shows that customer satisfaction, advertisements, word of mouth (WOM), and incentive offers/plans have a positive effect on increasing the potential customers. Thus, modeling the customer sensitivities to the price changes will help to construct a dynamic pricing system that optimizes profits while increasing demand market share and keeping high the level of satisfaction. Here, the functional framework of a generalized BM, presented by Ramírez-Hassan & Montoya-Blandón (2020) incorporating market effort into the BM, have been used for modeling demand adoption diffusion rate due to internal/external influences over the delivery-time axis. *F(t)* and *f(t)* are the cumulative and non-cumulative proportions of demand at offered delivery-time t, and Y(t) is the total number of potential customers demanding faster services up to but not including offers with delivery time t. The coefficient (*p*) is the rate of spontaneous demand adoption, and the coefficient (*q*) is the rate of imitation of demand adoption that the optimal *p* and *q* parameters for any order category computed by the algorithm in Figure 5. *T* is the set of all available delivery-time services which offered.

$$\frac{f(t_i)}{1-F(t_i)}=(p+qY(t_i))x(t_i),\quad x(t_i)=1+\alpha_1\frac{P(t_i)-P(t_{i-1})}{P(t_{i-1})}+\alpha_2\frac{\max\{0,A(t_i)-A(t_{i-1})\}}{A(t_{i-1})},\ t_i\in T \qquad (2)$$

Where $x(t_i)$, $P(t_i)$, and $A(t_i)$ are respectively the market effort, the price and the advertising for the i^{th} service offer with t_i promised delivery-time. These variables enter the market effort equation as percentage increases. The sale on offered service with delivery-time t_i will be computed by $S(t_i)=F(t_i)-F(t_{i-1})+e$, where *e* is an additive normally distributed error term with variance σ^2 and *F(t)* is given by equation (3).

$$F(t_i)=\frac{1-\exp\left\{-\bar{X}(t_i)(p+q)\right\}}{1+(q/p)\exp\left\{-\bar{X}(t_i)(p+q)\right\}},\qquad \bar{X}(t_i)=t+\alpha_1 Ln\left(\frac{P(t_i)}{P^{\min}}\right)+\alpha_2 Ln\left(\frac{\tilde{A}(t_i)}{A(0)}\right),\qquad t_i\in T \qquad (3)$$

Where $\bar{X}(t_i)$ is the cumulative market effort, found by transforming equation (2) into continuous delivery-time and integrating from 0 to t_i, and $\tilde{A}(t_i)$ is the last value for which there was a positive change in advertising ($P^{\min}$ is the minimum price that was offered among available services). Moreover, the time of peak sales defined as the time of the highest diffusion rate *S(t)* can be calculated by using the equation $t^*=(\ln q-\ln p)/(p+q)$ which means that decreasing/increasing in price, advertisement, and any other market effort on offering a service with promised delivery-time by t^* would have highest impact to increase demand on the corresponding order category.

6 Proposed scenario-based user-interactive application

We have conceived and developed a scenario maker application in MATLAB allowing us to set scenario assumptions through an interactive user interface, and to run the model under these assumptions to generate scenario-based probabilistic distributions of customer behavior. This includes probability distribution of customer preferences on different available offers for all categories and substitution probability for each offer when is not feasible. Aggregated, this results in scenario-based probabilistic patterns for hourly total demand volume for intracity, inbound, and outbound flows, to be transposed into orders in a simulated logistics system.

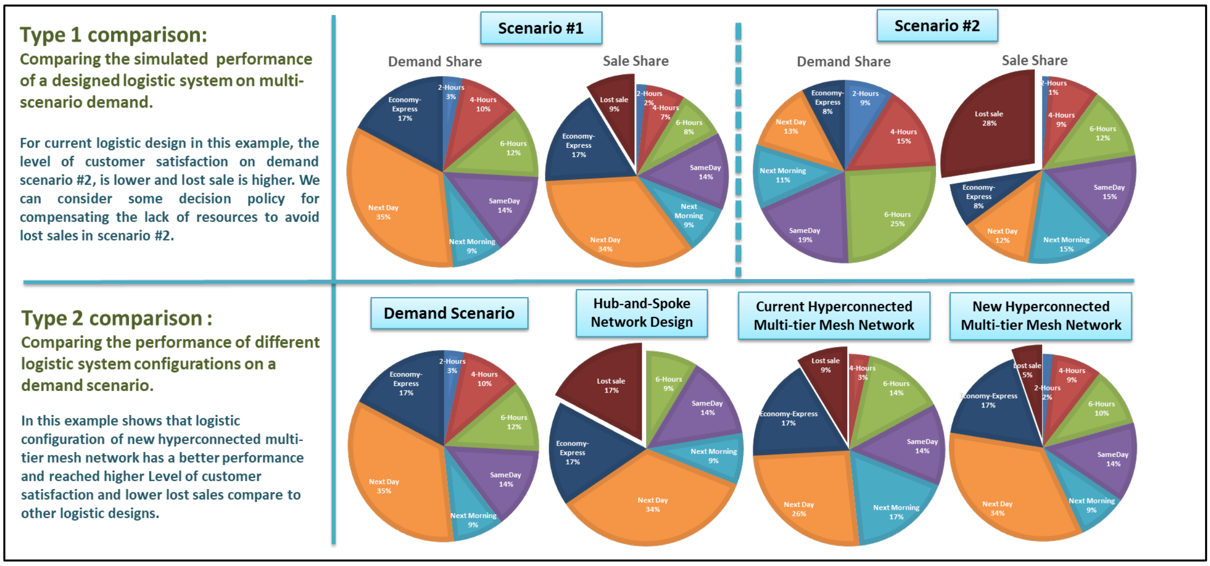

Figure 6: Beneficial outcomes of analysis over simulator results by feeding scenario-based probabilistic patterns for demand and customer behavior.

Using the scenario-based probabilistic models presented in sections 4.2, 4.3, and 5, and the probability distributions for source/destination of parcels on different time factors, enables to generate future scenario-based forecasted demand logs for the given time horizon which includes every single parcel request, as part of a demand scenario to be simulated. As depicted in Figure 3, alternative future logs based on alternative scenarios can be simulated in parallel worlds, and the results from these simulations combined to reveal and analyze logistics outcome and performance distributions. By using the demand and customer behavior models as drivers for the logistics simulator, it allows performing simulations jointly enabling to compare, beyond logistics costs and environmental impacts, the sales and customer satisfaction outcomes from different scenarios. Figure 6 provides examples of how feeding probabilistic patterns for demand and customer behavior helps holistically evaluating logistics system performance.

7 Conclusion

This study is a part of an industry-university project for a large urban parcel logistic system, focused on modeling and forecasting the intracity demand and within-city customer behavior to extend service offers for faster delivery. We proposed a scenario-based probabilistic modeling approach for demand generation to feed the parcel routing simulation model used for testing the performance of current/alternative logistic systems and monitoring the level of customer satisfaction. Moreover, a scenario-based application with an interactive user-interface has been described to make a wide range of various demand scenarios and to simulate customer preference on new services. This tool is resulting in scenario-based probabilistic patterns for demand and customer behavior which are feedable to the logistic simulator for testing performance and sales attributes as well as providing scenario-based forecasted demand logs for any arbitrary duration. Comparing multiple scenarios by analysis on demand logs is providing deep managerial insights on demand shape and its geographical distribution in terms of volume and service types, which is helpful to be prepared for future risks/challenges with suitable policies. Also, multi-scenario comparison by analysis on simulated sales after feeding probabilistic patterns leads to a better understanding of sale shape and its geographical distribution in terms of volume and service types and a better understanding about required capacities or lack of resources in different locations or different hours of the day which result to lost sales. Moreover, it helps comparing logistic performance for different hub/routing designs and the level of on-time delivery and customer satisfaction. Beyond the need for further empirical investigation of the paper's contribution, a key avenue for further research with high potential for model improvement is to explicitly account for customer satisfaction and its positive/negative impacts on future demand.

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