On-demand meal delivery: A Markov model for circulating couriers

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Introduction

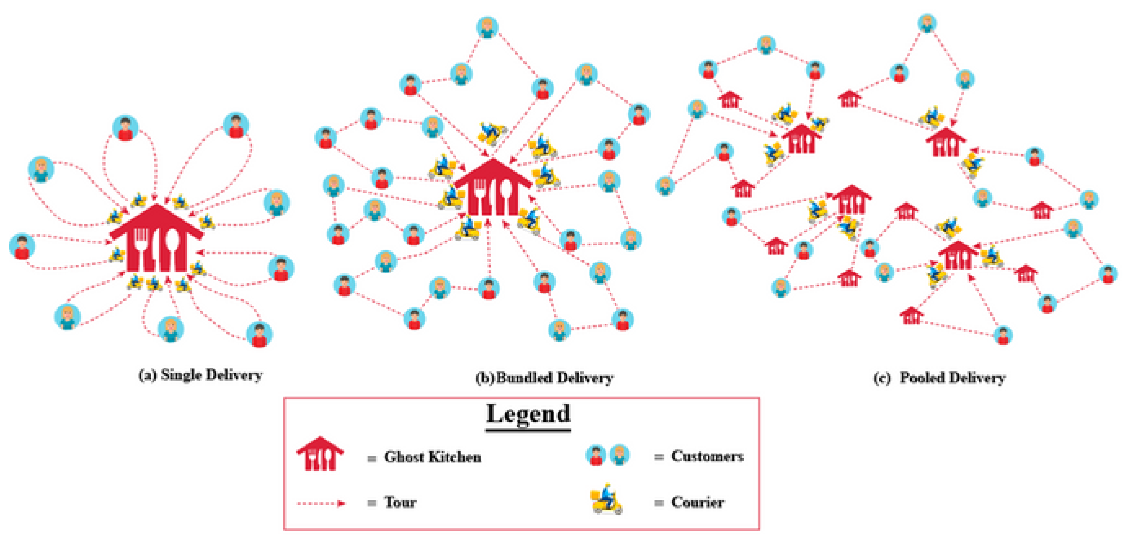
The rise of on-demand meal delivery logistics in urban areas, driven by technological platforms and accelerated by the recent pandemic, has brought about the emergence of ghost kitchen facilities designed solely for delivery. These facilities are strategically positioned near dense urban populations to optimise logistical efficiencies. Couriers, mainly using bikes, e-bikes, or scooters, are pivotal in this ecosystem. A significant challenge is creating a distribution system that ensures the freshness of ready-to-eat meals during timely deliveries. This study introduces a Markov model to represent the operations of couriers circulating to collect meals from kitchens and deliver them to customers. The model includes parameters reflecting the delivery context, such as urgency of delivery, kitchen attractiveness, and the locations of kitchens and customers. These parameters shed light on the dynamics of on-demand delivery. The study also illustrates the insightful application of the Markov model, including the potential effects of relocating a kitchen which is useful to strategic planning.

Objective

The study employs a Markov model to analyse on-demand meal delivery logistics which aims to estimate delivery time and assess ghost kitchen attractiveness. By integrating stochastic courier movements, travel times and order distributions we seek to understand the on-demand delivery dynamics which will in turn, provide actionable insights for restaurant location optimisation and urban planning.

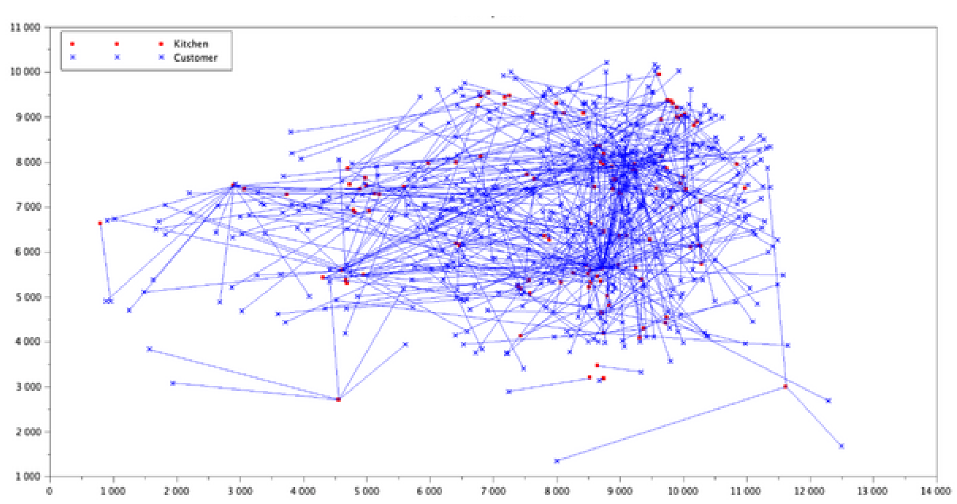
Methodology

The methodology employs a Markov model to simulate the circulating couriers in an on-demand meal delivery system. This model is structured with $n + 1$ parameters, where 'n' represents the combined count of kitchens and customers. Each entity (kitchen or customer) is associated with a parameter denoting courier demand. Additionally, an "urgency of delivery" parameter, β is incorporated. The model will then be able to to compute both the mean and variance of delivery times. To ensure its accuracy, the model undergoes a calibration process using two procedures: one that matches courier visit probabilities with order probabilities, and another that reproduces a specific delivery time. Calibration is exemplified using a Grubhub dataset. Couriers may only make one, one or two drops, or up to infinitely many drops (however very unlikely).

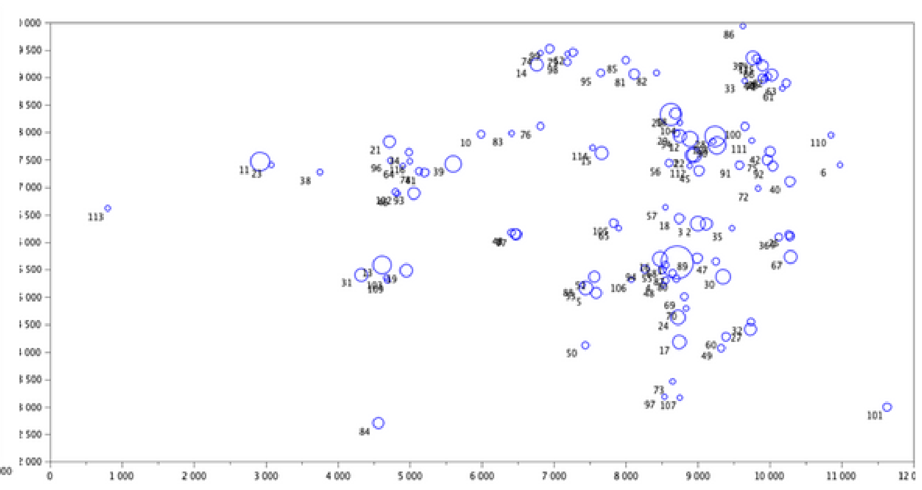


Delivery types when studying on-demand food delivery logistics.

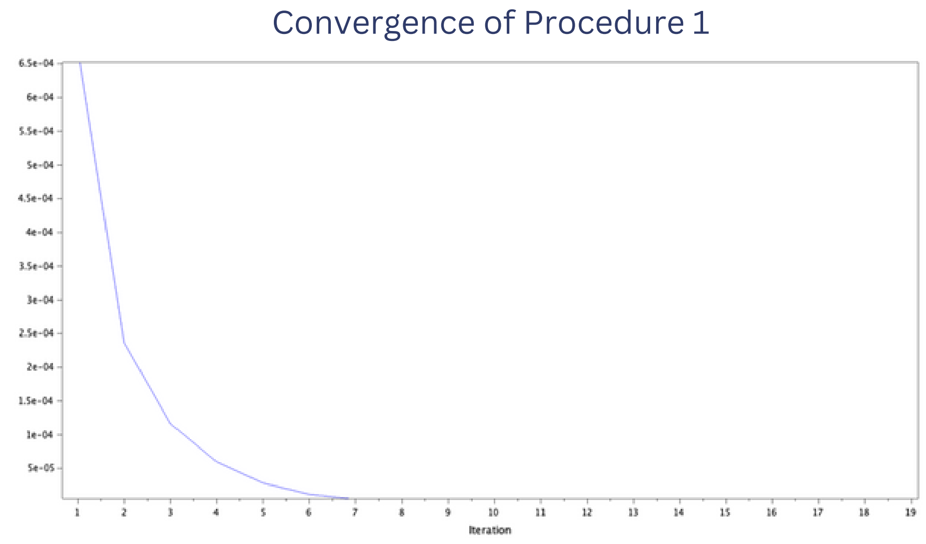
Kitchen and Customer Locations



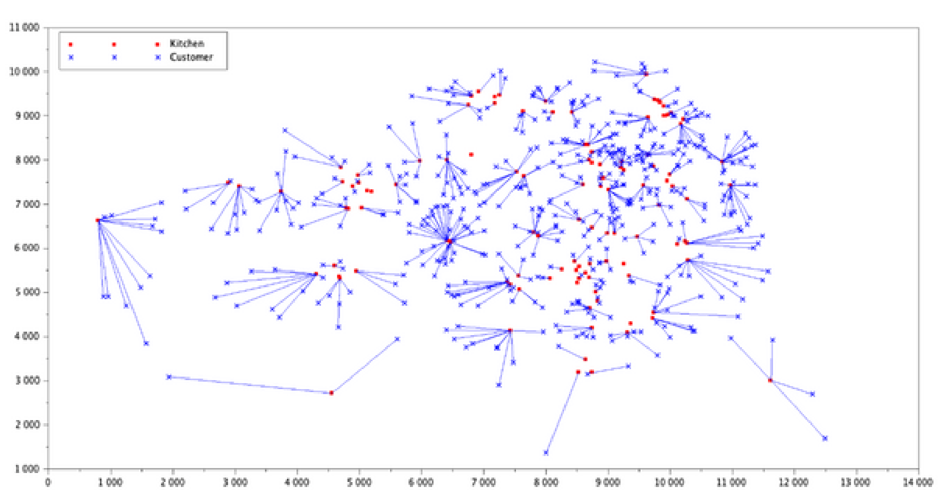
Representation of Number Of Orders By Circle Diameter



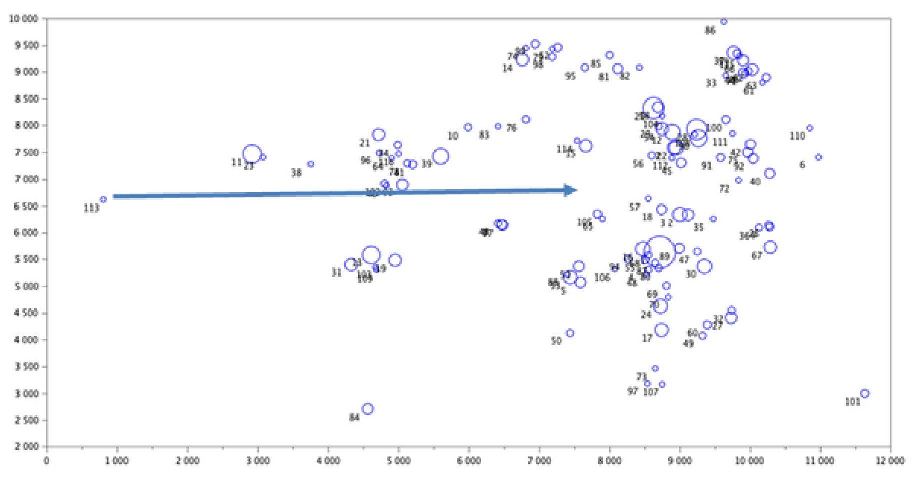
Convergence of Procedure 1



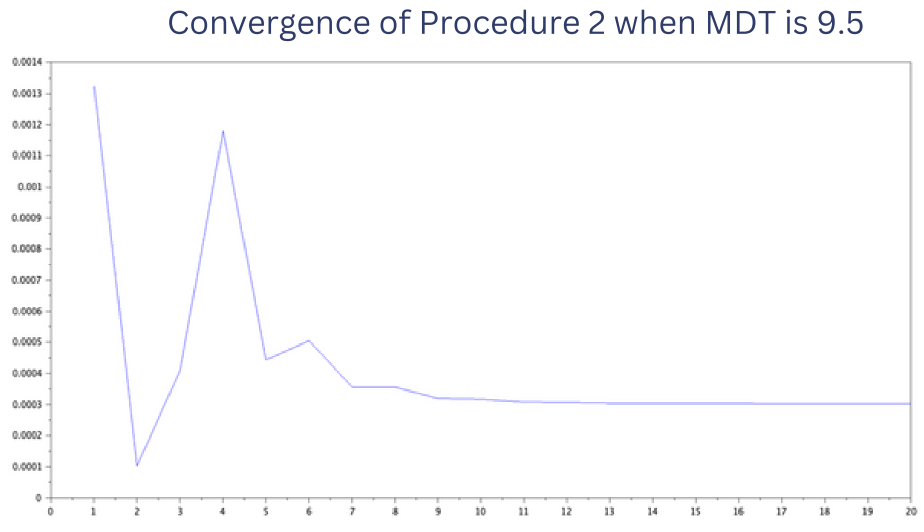
Orders Assigned to the Nearest Kitchen



Horizontal Relocation of Kitchen Example



Convergence of Procedure 2 when MDT is 9.5



Results

In the numerical example, data was retrieved form the the Grubhub dataset https://github.com/grubhub/mdrplib which includes 116 kitchens and 505 orders. The city from which the data emanates is not specified to preserve confidentiality, so it is unfortunately not possible to relate locations to a road network. The orders tend to be placed with the nearest kitchen, but not always so. From the results, there is clearly a clustering of kitchens, evidence that successful kitchens attract competitors. The clustering of kitchens also corresponds to the clustering of customers. From the two procedures, Procedure 1 rapidly converged, with perfect alignment between modelled and observed order frequencies achieved by the 14th iteration, yielding β = 0.38 and a mean delivery time of 8.86717 minutes. Procedure 2 validated these results, returning the same β value when the mean delivery time was set to 8.86717 minutes. However, discrepancies arose when different mean delivery times were specified, leading to variations in β but not achieving perfect alignment with observed order frequencies.

Discussion

Couriers' movement can be depicted as a random walk, navigating based on a transition matrix where the transition probabilities are dependent on travel time and order probabilities at destinations. There is as an indication that there is a preference for ordering from proximate kitchens, but with exceptions. Some kitchens might receive no orders if proximity was the sole factor. Insights such as relocating a kitchen can be analyzed. For example, relocating kitchen 113 from the periphery to a central location increases its demand by a factor of 2.85, or almost three times, all else remaining equal. Although the model isolates intrinsic attractiveness (**q**) and delivery urgency (**β**), they are somewhat interconnected. Adjusting one affects the other. Another utility is the model's capacity to generate an origin-destination matrix for couriers. In many cities, e-bike couriers dominate on-demand deliveries. Thus, if a city's street layout is available, courier flow can be mapped, highlighting key streets or junctions. Regrettably, with the Grubhub dataset, the specific city remained unidentified to our team.

Conclusion

The results of the analysis based on real on-demand meal delivery data show that the most favourable location for a ghost kitchen generally lies in a central location. Through our results, the study underscored the significant effects of kitchen location on demand, laying a foundation for future optimizations in the meal delivery domain.