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Data-Driven Reserve Personnel Placement to Balance Operation Default Risk and Resource Utility

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Abstract. In last mile delivery, to manage delivery default risks and ensure delivery completion, reserve personenel are placed. This is due to driver procurement having to be planned and executed about one-month ahead, when delivery demands could only be roughly predicted. Although reserve drivers occasionally work as final defense, it regularly lowers driver utility, and a method to place reserve drivers balancing delivery default risk and driver utility is required. Previous work tackled this problem by stochastic staffing problem approaches, but there existed a limit in feature modelling and result interpretability, which created a gap in algorithms and procurement manager decision making. The proposed method aims to fill this gap, by taking a transdisciplinary approach of traditional scheduling, probability modelling, and explainable AI. In doing so, a flow of first creating a staffing schedule based on fixed staffing number demands, and then determining a fixed number of reserve personnel required for each staffing window, was designed. A probablity distribution of required personnel number per delivery is calculated in doing so, and this distribution is used as a easy to understand decision support tool for delivery managers. Through a case study using delivery demand data of a Japanese EC-logistics company, the proposed method was shown capable of lowering reserve drivers, with having a high potential of no delivery defaults.

Keywords: Human Resource Planning, Demand Uncertainty, Operation Default Risk, Risk Management, Last Mile Delivery, Decision Support

Introduction

In last mile delivery, to manage delivery default risks and ensure delivery completion, reserve personenel are placed. This is due to driver procurement having to be planned and executed about one-month ahead, when delivery demands and other conditions could be only roughly predicted. Reserve drivers work as final defense when delivery demands spike or other operation troubles occure. However, these only events only occure occasionally, and therefore reserve personnel regularly lowers driver utility. The balance of this risk-utility trade off is currently decided according to each driver procurement manager's experience. This decision making process is stressful and inaccurate at times, which calls for a data driven approach to support this decision making.

Previous work have addressed this problem in terms of stochastic staffing problems, by bulding up on traditional scheduling algorithms. Traditional scheduling algorithms dates back to the 1950s, starting with optimization of cost and service level [1]. Futher conditions were modelled with mixed integer programming on fixed objectives and

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constraints as done by Venkataramana and Brusco [2]. As the problem became complex considereing scenarios such as rerostering, heuristic methods were introduced as in the work by Pato [3]. Following this, the problem setting was further complicated to non stationary, stochastic staffing problems [4]. In this context, Bagheri considered uncertainties in management objectives and staff preferences using sample average approximation(SAA) [5]. A dynamic adjustment approach was taken by Aydas using two-stage staffing adjustment [6]. Legran utilized the primal-dual algorithm and SAA to create a effective nurse rerostering plan [7].

The challenge, and therefore mathmatical limitations in these research was for the optimization algorithm having to output staffing schedules based on vague demands, rather than fixed staffing number demands as in conventional problem settings, leading to complex modelling and large scale computations. Also, due to this complexity, the reasoning for the output staffing schedules were hard to interpret, creating a gap between the algorithm and procurement manager in decision support.

In this paper, we aim to make the stochastic staffing problem computationally and interpretability simple, by taking a transdisciplinary approach of established traditional scheduling, probability modelling, and explainable AI [8]. The approach first creates a staffing schedule based on fixed staffing number demands. Follwing this, a fixed number of reserve personnel required for each staffing window is determined. The overall flow is shown in Figure 1. This process aligns with the decision making in staffing so far, with the reserve personell number per staffing window acting as an easy-to-understand interface between the staffing algorithm and procurement manager.

The main idea of this paper, is to plan reserve personnel based on the probablity distribution of required personnel number per delivery, and interact with the procurement managers to set a risk tolereance threshold in the distribution, finalizing the number of reserve personnel. Through this process, data driven risk management decision support for driver procurement could be realized.

Our contributions are as follows.

1. Propose a model to support required reserve personnel decisition making number per day (Chapter 1)
2. Analyze demand quantity and driver throughput from actual delivery data, and define main features leading to uncertainties(Chapter 2)
3. Validate the proposed method's effectiveness through a case study on actual delivery operation data, and driver procurement manager feedback. (Chapter 3)

1. Daily reserve personnel decision making model

1.1. Overall staffing flow and scope of this paper

The overall staffing flow in shown in Figure 1. The flow starts with creating a base staffing schedule from expected required drivers, per day per delivery area segmentation. Following this, reserve personnel is added to the schedule.

Creating base staffing schedules is assumed to be done with established, high speed methods. If the constraints are simple and could be mathematically modelled without dropping any information of the constraints, solvers such as gurobi [9] could be used. On the other hand, if constraints are comples, heuristic algorithms such as genetic algorithms could be used [10].

The main scope of this paper is the following section of adding reserve personnel to the base schedule. There is a preprocessing, and serial process in this scheduling. In the preprocessing phase, based on past rain and delivery data, delivery demand and throughput distribution is calculated per feature. Based on these preprocessed and learned distributions, reserve personnel is calculated. This second process is done serially, according to the timing of forecast data acquisition. For example, rain forecast data could be acquired only a week before the actual delivery date.

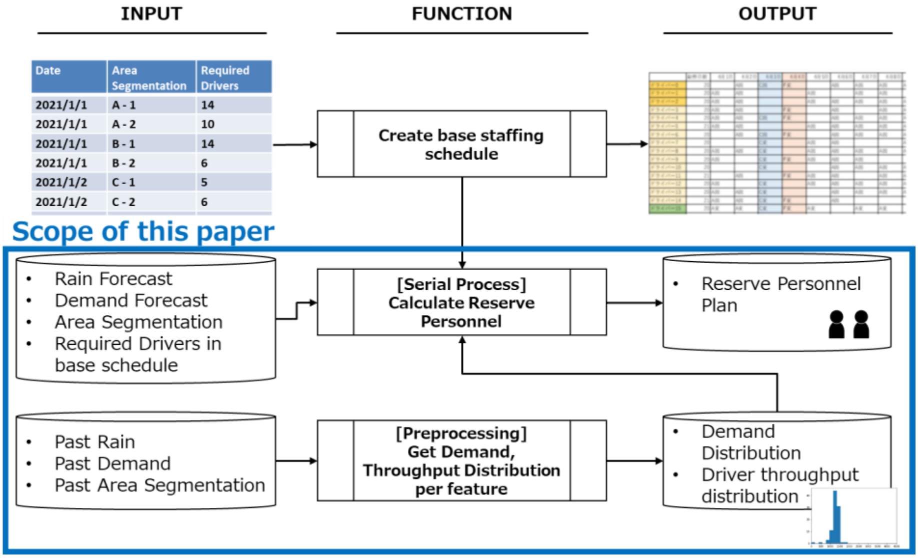

Figure 1. Overall flow of Staffing.

1.2. Reserve personnel decision making

Required personnel could be divided into demand quantity, and driver throughput, as shown in Equation 1. In daily operations, these two factors fluctuate due to certain features, occasionally leading to reserve personell action.

$$TotalPersonell = DemandQuantity / DriverThroughput \tag{1}$$

Therefore, the distribution of required drivers could be modelled as a combination of delivery demand distributions, and per driver throughput distributions, as shown in Figure 2. Further, required personnel could be set as the difference between the currently scheduled persons number, and a risk hedged persons number. The risk hedged persons is set as the β percentile of the distribution. This β could be set by procurement managers after obserbing the distribution and overall result.

The calculation shown in Figure 2. is conducted for each delivery area segmentation, and the total reserve personnel is calculated as shown in Equation 2.

$$ReservePersonell = \sum_{area\_segment}(Num_{risk_{hedged}} - Num_{current}) \tag{2}$$

1.3. Distribution generation flow

The required driver number distribution is created by sampling N_sample times demand, throughput values from the distributions, and using equation 1. to calculate the needed driver number. In doing so, parameters α percentile and $n\_min\_throughtput$ is defined as the lower bound of sampling in driver throughput. This is because driver throughput is not at its 100% at ordinary times, and sampling from above a certain threshold helps to more express driver maximum throughput. $n\_min\_throughtput$ is additonally set to α percentile, because per driver throughput distributions are long tailed at times, which leads to underestimation of driver throughput.

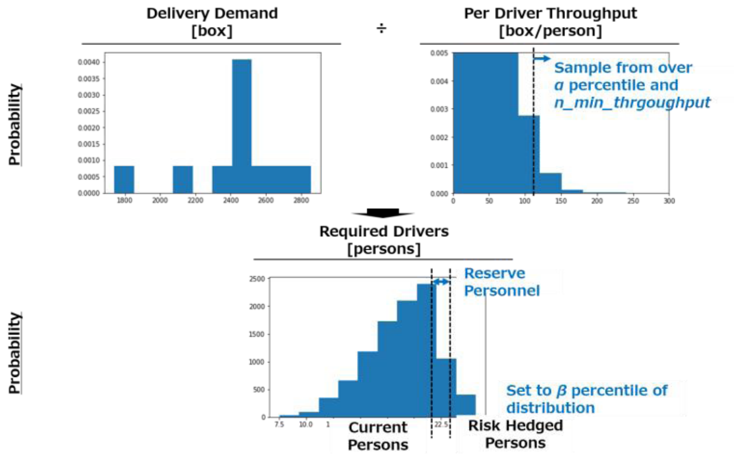

Figure 2. Reserve Personnel Calculation Flow.

The demand and per driver throughput distribution is expressed by the fequency distribution these values, aggregated according to features of each delivery round conducted by the drivers. In the following section, these features are introduced with data analysis results.

2. Demand quantity and driver throughtput distribution analysis

2.1. Analyzed data and overall result

Delivery data of Setagaya-Ward, Tokyo from 2019/5/20 to 2021/5/31 of a Japanese EC-logistics company was used as analysis data. The data items are as listed below.

- Date
- Delivery Round Time … i.e. AM or PM
- Delivery Area Segmentation
- Destination (id, address, latitude, longitude)

Setagaya-Ward consists both of company delivery destinations, and individual person delivery destinations. Company destinations do not have a specified delivery time window, and could be delivered any time in the working hours. On the other hand, individual destinations frequently have a desired delivery time window of 2 hours. This results in driver throughput difference, which would be mentioned in section 2-3.

The overall result of demand, throughput distribution features are shown in Figure 3. Similar to time window ratio mentioned above, features of delivery density, and rain amout affect per driver throughput. For per driver throughput distribution shape, which corresponds to the skirt width of the distribution, the combination of delivery density and rain amout was shown to be having most impact.

For delivery demand, additional to basic features of day of week, delivery round time, delivery area segmentation and is holiday in definite value prediction, the feature of weekdays having a holiday in the same week was shown to have higher standard deviation compared to ordinary weekdays.

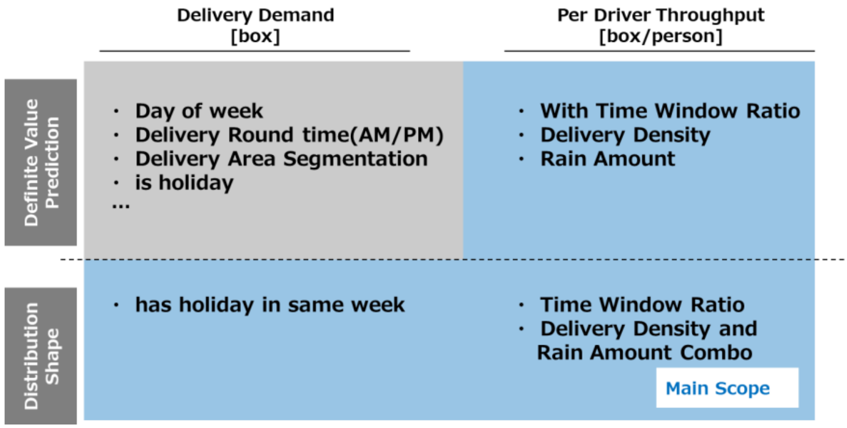

Figure 3. Demand, Throughput distribution features.

2.2. Demand

Figure 4. shows a scatter plot of the mean and standard deviation of number of delivered boxes per weekday (Monday, Tuesday, … Sunday) and per having a holiday in the past same week. For example, if Wednesday was a holiday in a week, the following Thursay to Sunday is flagged as having a holiday in the past same week.

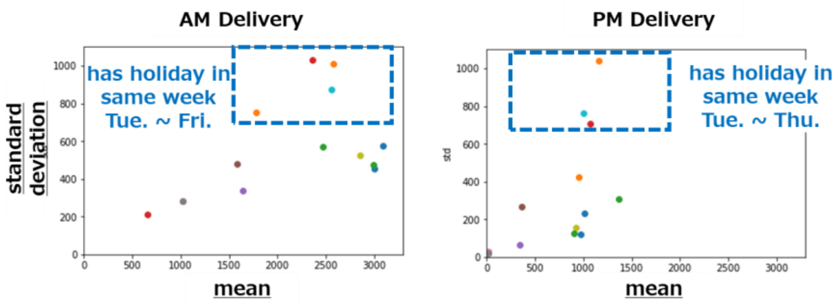

Figure 4. Per day of week / Per having or not having a holiday in the same week, scatter plot.

It could be seen that basically, the standard deviation rises as the mean rises, which is natural. Further looking at the plots with high starndard deviation, it was shown that these plots are weekdays having a holiday in the same week. This phenomenon could be explained as people’s customary package ordering action to change with a holiday inserted in their daily routines.

2.3. Driver throughput

Figure 5. upper side, shows a scatter plot of between features of with time window ratio, rain per hour, average distance between destitation, and throughput. It could be seen that as these features rise, the maximum throughput drawn in the red line decrease. Figure 5. lower side, shows the frequency of the throughput per each feature intensity. The thresholds for the intensity flag was set as below.

- With time window ratio
    - 0.8 or above: High
    - Below 0.8 and above 0.4: Moderate
    - 0.4 or below: Low
- Rain per hour
    - Above 1mm per hour: High
    - 1mm per hour or below: Low
- Average distance between distination
    - Above 900 meters: High
    - 900 meters or below: Low

It was shown that the distribution shape differs according to with time window ratio, and the combination of rain per hour and average distance between destinations. A high ratio of time windows create a strong constraint in delivery, and results in a spiked shape of distribution, for other constraints such as geological positions of destinations are drawn out. Vice versa could be said for low ratio of time windows. The distribution shape difference of combination of high rain and low or high distance between destinations, could be explained by delivery action change in drivers. In high density areas, drivers tend to park their vehicle, and visit numerous destinations in one parking action. However, in the case of high rain, activity outside the vehicle starts to get limited, leading to a decrease in the per park numerous delivery action. This action change, results in the change of distribution shape.

As shown in section 2.2 and 2.3, distribution shape change results from a major event leading to customer or driver action change. Additional to general features mentioned above, domain specific features resulting from unique operations or systems may be added to further make accurate the distributions.

3. Case Study

3.1. Used data

Additional to delivery data of Setagaya-Ward, Tokyo from 2019/5/20 to 2021/5/31 mentioned in Sectoin 2-1, rain per hour data of Tokyo within this period was used for the preprocessing phase.

For the planing phase, the staffing schedule from 2021/11/1 to 2021/11/30 was created. Rain per hour results were used as the forecast data, with the assumption that the forecast is always correct. To derive the base staffing persons number for each day, a demand forecast model ensembling boosting methods was used. The demand forecast for each delivery area was divide by a constant of 60 boxes per driver throughput, to obtain the required driver number in the base schedule. This constant 60 was set by the driver procurement manager in the logistics company, as to express the heuristic nature of the base schedule. Similarly, $n\_min\_throughtput$ was set as 30, simply half of the above values. As shown in Figure 6. , with time window ratio and average distance between destination features were not used here, for a simple forecaset model could not output a fine meshed data of destination attributes or geological positions. Leveraging these features is future work and in progress.

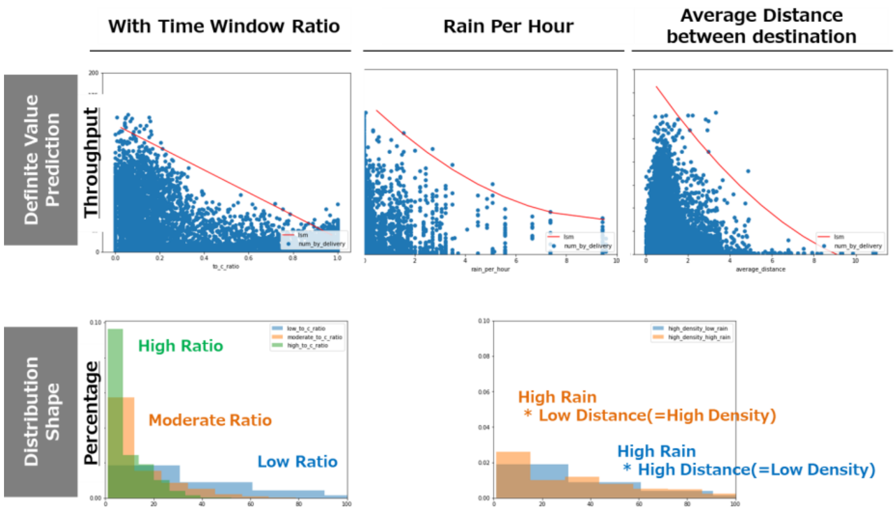

Figure 5. Above: Scatter plot of per driver throughput and feature number. The red line is a 2 dimentional least square fitted line, of the maximum throughput per unit. Below: Fequency of throughput for each feature intensity. The thresholds are as stated in the paragraph.

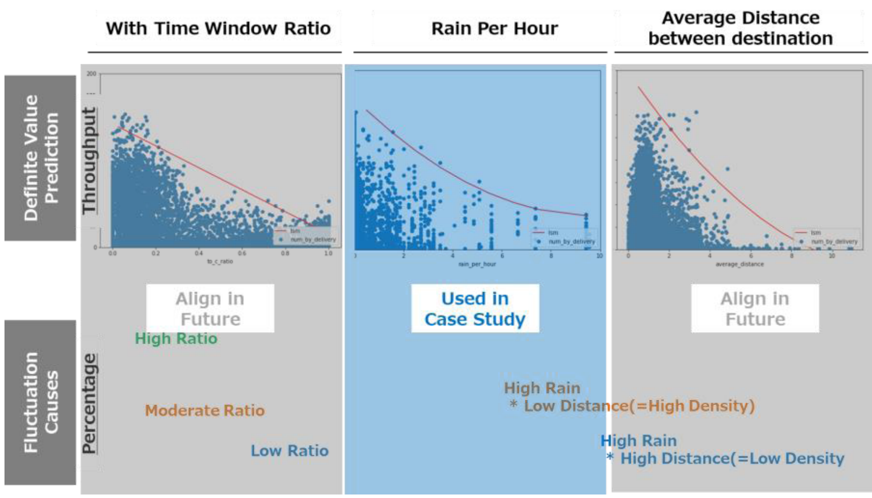

Figure 6. Used features in case study mapping.

The lower bound percentile of sampling driver throughput α was set as 96%. Three values of 96%, 97%, and 98% was set for risk hedged persons β percentile as to simulate the situation of interactive β setting by the procurement manager. The sampling ireration number in driver number distribution generation N_sample was set as 10,000.

3.2. Results

The comaprison of current and new proposed reserve personnel number for each β is shown in Figure 5. In the overall trend, the suggested reserve personnel number of Saturday PM with a holiday in the same week spikes. Additional spikes emerge as β becomes larger. Viewing this overall result, the the procurement manager could first decide the initial β selection based on current operation status, and then further look in to the reasoning of each result, to fix the needed reserve personnel. For example in this case study, β being 97% was seen to be close to the current operation, and examined in detail.

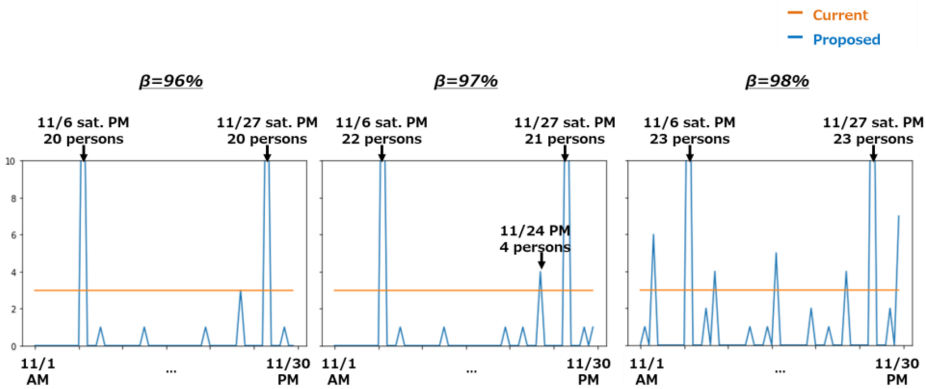

Figure 7. Current and proposed reserve personnel number in 2021/11/1 ~ 2021/11/30 Setagaya-Ward (11/3, 11/23 are holidays).

Further distributions when β is 97% is shown in Figure 7. and Figure 8, showing the reasoning of the reserve personnel spikes. In Figure 7, 11/6 sat PM, the required driver distribution is wide ranged, resulting in the spike of 22 persons in reverve personnel. This is due to the demand distribution being sparse, and the throughput distribution also being long-tailed. Through this data shortage, this spike could be interpreted being due to lack of cumulated data for this feature date (Saturday PM having a holiday in the same week), and the suggested value could be set as a reference value. The same interpretation could be done for 11/27 sat. PM.

For Figure 8., 11/24 PM, a Wednesday with a holiday in the same week, the upper range of the distribution could be seen as packed, which is due to the proposed method preparing for the case of demand spikes. This suggestion could be seen reasonable, and the suggested value should be adopted. The remaining decision to be made by the procurement manger is the setting of β, regarding current occupancy rate of the 3 reserve personnel in the current operation, and cost which could be assigned for risk management.

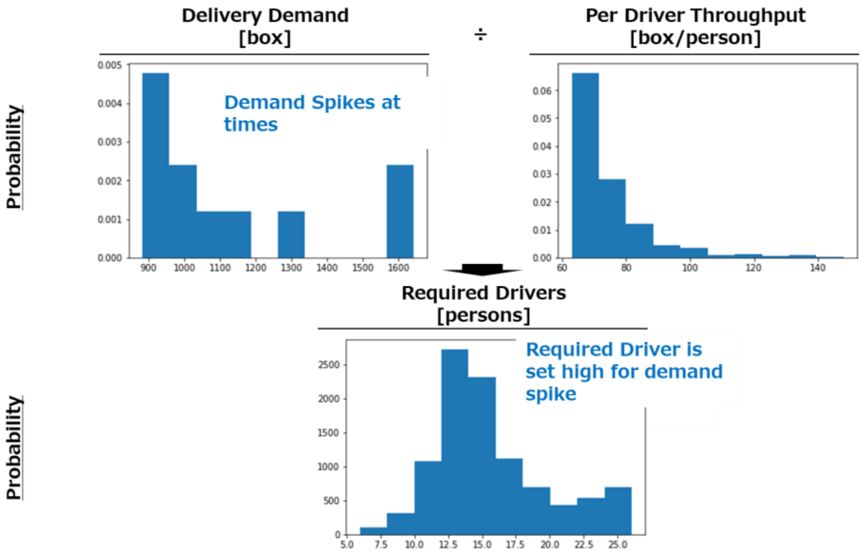

Figure 8. Demand, Throughput and Required Driver distribution for 11/24 PM, Delivery area A, $\beta = 97\%$

The resulting plan based on $\beta = 97\%$ was seen reasonable by driver procurement manager, suggesting this overall flow to have a high potential of low delivery defaults. Through this process, the number of reserve personnel could be decided in a data driven way.

Discussion points for further deepening are below.

- Obtaining actual reserve personnel action logs within the case study period, and analyzing further cases with the need of reserve personnel. There may be cases out of scope of the generated distribution, such as absense of a driver, which is more likely in recent social situations of COVID 19.
- In association with the above, identify cases where existing methods, and the proposed method initially creates personnel scheduling not aligning with the actual personnel action, and investigate how the proposed second stage of manager interaction could make the schedule finer
- A method of leveraging with time window ratio and average distance between destination features could be also deepened. Most demand forecast models output the demand number, and not the attributes. Attribute forecasting raises the difficulty of the forecast task, and a way to approximate this needs to be considered.

4. Conclusion

In this paper, to make the stochastic staffing problem computationally and interpretability simple, a transdisciplinary approach of transdisciplinary approach of traditional scheduling, probability modelling, and explainable AI was taken. In the propsed flow, first a staffing schedule based on fixed staffing number demands was created, and then a fixed number of reserve personnel required for each staffing window was determined. This process and reserve personell number acts as an easy-to-understand interface between the algorithm and procurement managers, for it aligns with decision making so far.

The proposed model creates a required driver number distribution for each delivery round and area segmentation, which could be used with cooperation of driver procurement managers to set a risk hedged driver number. This difference of the current planned driver number, and risk hedged number, is set as reserve personnel. In creating this driver number distribution, delivery demand and per driver delivery throughput distributions were estimated, and to finely do so, features affecting the distribution shape was defined through analysis. Based on these features, the demand and throughput distributions were created with frequency distributions of data aggregation based on the features. A case study was conducted to a Japanese EC-logistics company data, and results show that the proposed method could more efficiently place reserve personnel compared to the status quo, with a high potential of no delivery defaults.

Future work is obtaining actual reserve personnel action logs within the case study period, and analyzing further cases with the need of reserve personnel. Also, a method of leveraging the feature analysis method further is required, for a simple forecaset model could not output a fine meshed data of destination attributes or geological positions.

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