Efficient Resource Management: Elevating New York City Fire Department Operations

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***Abstract*—This paper presents an integer linear optimisation model designed to enhance the resource allocation and emergency response in an efficient manner of the Fire Department of New York City (FDNY). Given the complexity of managing a vast amount of resources across the five different boroughs of the city, our model aims to optimize the distribution of fire vehicles to improve service coverage and response times, taking into account scarce resources, political disputes, and displacements between stations. Our approach utilized historical incident data, station capacities and inter-station distances to formulate a comprehensive optimisation problem. The model strategically positions engine, ladder, rescue, squad, and hazmat companies to ensure rapid and equitable emergency response across all neighbourhoods. Experiments conducted with various solvers were made to compare the performance and rapidness finding a solution in the aforementioned problem, concretely CBC and SCIP in their Mixed Integer Programming variant, and CBC outperforms SCIP in this case. Apart from the optimal value given by the optimization function, graphical representations have been made to draw conclusions about the efficacy of the proposed model, ensuring that it returns a solution which satisfies every need.**

***Index Terms*—Multi-Objective Optimization, Integer Linear Programming, Allocation Problem, Emergency services distribution**

I. Introduction

As the largest fire department in the United States and the second-largest in the world, the Fire Department of the City of New York naturally operates within a framework of considerable complexity in both organization and resource management. At the operational level, the Fire Department is organized in five distinct companies where each one of them offers a different type of vehicle: engine, ladders, rescue, squad, and hazmat. Moreover, it has a total of 218 stations distributed throughout the city, where these vehicles are located in. However, the department operates under two distinct shifts: the night shift and the day shift, adding a layer of complexity to the decision-making process for the allocation of these vehicles. Indeed, this article aims to present an optimal solution to the placement of these vehicles, as well as the assignment of service to New York neighborhoods. Following this introduction, the article explores the results and insights derived from previous works that have addressed similar issues. Subsequently, our optimization approach is introduced with some context considerations and also, its implementation is discussed. Finally, the objective and results of some experiments carried out are presented, in addition to the final conclusions of the developed optimization model, along with considerations for future work.

II. Related work

Exploring the context of our research and examining proposals put forth by others, we aim to provide a comprehensive overview of the methodologies and findings that have laid the groundwork for our optimization model.

For example, [1] addresses the problem of urban fire station siting and expansion in response to urban growth and development using integer programming, specifically the Maximal Covering Location Problem (MCLP) and its extensions, to address the balance between service coverage and cost. These models are designed to maximize the coverage of service demand within a given response time (9 minutes for 90% of the calls as per the National Fire Protection Association (NFPA) [7] standards) while minimizing the number of fire stations required. This criteria will also be used in our optimization model, as it takes an important role when deciding where to allocate a fire station. The paper also investigates the Threshold Coverage Model, a combination of Location Set Covering Problem (LSCP) and MCLP, which directly incorporates the service coverage requirement by minimising the number of fire stations necessary to cover all demand; and the Complementary Threshold Coverage Model, which addresses spatial data representation issues by allowing partial coverage of demand points. This makes it potentially more suitable for applications where the spatial distribution of demand and the coverage provided by facilities are complex and cannot be adequately represented by a binary coverage assumption. While the paper targets fire station allocation and our project deals with vehicle allocation, both require spatial optimization and discrete optimization techniques. The paper's focus on response times and coverage, contrasts with our project's additional constraints like vehicle capacity and shift scheduling. Despite these differences, the paper's methodology could inform spatial optimization and service standard considerations in our project.

In [2] can be seen the methodology used to tackle the problem of defining an efficient ambulance deployment strategy, that adapts to changing demand, traffic conditions and uncertain service requirements in a city setting, which has a tight relation with our problem. The authors confront this problem by trying to minimize the overall cost associated with relocating ambulances between waiting stations in consecutive time intervals. The objective function used served us as inspiration, as later will be discussed, since we applied a minimization of the cost of not sending a vehicle to an emergency, from a station. At a glance we can see that both problems are pretty similar, that's why we chose this article. Furthermore, we could extract some ideas to expand our problem and do it better. Right now we do not have available data of the traffic conditions, even though it has a big influence in the time taken to reach the emergency. Peak hours and off-peak hours could be studied, which can improve the allocation of the vehicles in the neighborhoods.

Meanwhile, an alternative approach is presented in [3], introducing a bi-objective spatial optimization model along with a constraint-based solution procedure that derives Pareto solutions. This method facilitates the exploration of diverse scenarios for fire station locations. The primary focus of this model is on two important aspects: accessibility and service coverage. Our case study did not incorporate the accessibility dimension, given the unavailability of geographical and traffic data. Addressing this gap in future research could offer valuable insights into optimizing fire station locations. Furthermore, the integration of both accessibility and service coverage concerns through the extension of the constrained PMP model represents an interesting addition to the existing body of research in the field. This novel dimension not only enriches our understanding of fire station siting strategies but also sets the stage for more nuanced and comprehensive approaches to urban and regional planning, steering the field towards more effective and resilient emergency response systems.

Regarding the information in [4], there are two main forms of dealing with a multi-objective optimization problem (MOO) without complex mathematical formulations. The first one consists of Pareto solutions, where each aspect of the solution is maintained independent and a trade-off among them is found. The second one is scalarization, which compacts all the objective function in a single one, adding the solutions which will be maximized and subtracting the one we need to minimize. Pareto solutions require especial methods of comparing the solutions in order to select the optimal one and evolve, while scalarization methods determine weights for the objective functions before solving the problem. Nevertheless, the most significant aspect that links this paper with our work is the fact that scalarization normalizes the objective functions. We do not combine maximization and minimization functions, but we do have a combination of minimization functions in different scales (estimated demand left unattended, estimated cost depending on distance and demand, and displacements between shifts), and the normalization technique proposed in [4] solves this problem.

Finally, [5] addresses the joint optimization of location and assignment for multi-type fire vehicles. It employs a Mixed Integer Linear Programming (MILP) algorithm with Gurobi as the solver to minimize the overall system cost, encompassing facility construction, operational expenses, and fire damage losses. It defines a fire/incident cost which is derived from the vehicles response times and fires duration in historic data. They consider up to three operational costs to minimize (travel, fire damage and installation cost), which coefficients, instead of being computed specifically for their case, are derived form literature [6]. In our case, for example, the distance traveled by vehicles in the shift change or the cost in terms of equality amongst other considerations. The same way, constraints that involve computations of needs of specific vehicles for certain incidents could be translated to our problem or the avoidance of over-assigning vehicles of certain types to incidents. Also, considerations like a minimum response time for incidents will be taken on board, as was discussed in [1].

III. Proposed Model

Emergency services, as is the case of the fire department, are departments that seek both to serve as many people as possible and in the shortest possible time. The former is due to the fact that it is a service for all citizens, so leaving any area uncovered would have significant negative effects on the image of the service. The second, but not least important, is that in case of emergency, it is advisable to act as quickly as possible to minimize the damage to both city's infrastructures and human lives.

New York City is comprised of its five major boroughs: Manhattan, Brooklyn, Bronx, Queens and, Staten Island. Each one of them have its chiefs and representatives, who seek to respond to the needs of their stakeholders. Nevertheless, the reality is that each of these boroughs is an influence group within the local and operational decisions of the department. As a fact, strongly favoring any one of the boroughs in service planning would mean major tensions and internal and external complaints.

In addition, for scarce resources such as squad or rescue companies, it is better not to group them in the same location, since they are mean to cover a wide geographic area. If a single borough concentrates all vehicles of the same type, it would again cause tensions within the department and at the city council level. Therefore, it has been suggested that the planning should consider the multi-district nature of New York City. Although there is an exception: the hazmat vehicle, since only one of these resources is available.

In the eyes of the local administrators, it would also seem strange that when a station accommodates more than one vehicle, it contains all vehicles of the same type. This gives a sense of miss-allocation of available resources since those extra vehicles could be used to increase the area covered by the department.

Also, we should keep in mind that there are different types of emergencies covered by the fire department. That is, any vehicle cannot be used for everything. The frequency of these emergencies can be affected by different factors, both temporal and structural.

At shift change, vehicles should not travel long distances, as this causes a sense of increased work and fatigue for the workers when making the trip between stations.

A. Model specification

The proposed linear optimization model includes a preference to not leave any area uncovered, but also that any emergency can be responded to within a time frame of less than 9 minutes. Also, it accounts the problem of allocating more than one vehicle of the same type in the same station or even borough, but making exceptions with: the hazmat, squad and rescue vehicles. Then, it faces the shift issue penalizing long travel distances to others stations. Consider the following parameters:

$I, J, K, L.B$: set of shifts, types of vehicles, neighbourhoods, stations, and boroughs, respectively;

i, j, k, l, b: index of shifts, types of vehicles, neighbourhoods, stations, and boroughs, respectively;

X_{ijkl}: number of vehicles of type j (except hazmat, squads, and rescues) assigned to station l to serve neighbour k in shift i, where:

$$X_{ijkl} \in \mathbb{R}, \quad i = 1 \dots I, \quad j = 1 \dots J, \quad k = 1 \dots K, \quad l = 1 \dots L;$$

N_{i,l_1,l_2}: number of vehicles transported from station l to station l_2 in the shift change i, where:

$$N_{i,l_1,l_2} \in \mathbb{R}, \quad i = 1 \dots I, \quad l = 1 \dots L, \quad l_2 = 1 \dots L;$$

$$Y_{H_{li}} = \begin{cases} 1, & \text{if vehicle Hazmat is assigned to station } l \text{ in shift } i \\ 0, & \text{otherwise} \end{cases}$$

$$\text{with:} \quad Y_{H_{li}} \in \{0,1\}, \quad i = 1 \dots I, \quad l = 1 \dots L;$$

$$Y_{S_{li}} = \begin{cases} 1, & \text{if a Squad is assigned to station } l \text{ in shift } i \\ 0, & \text{otherwise} \end{cases}$$

$$\text{with:} \quad Y_{S_{li}} \in \{0,1\}, \quad l = 1 \dots L, \quad i = 1 \dots I;$$

$$Y_{R_{li}} = \begin{cases} 1, & \text{if a Rescue is assigned to station } l \text{ in shift } i \\ 0, & \text{otherwise} \end{cases}$$

$$\text{with:} \quad Y_{R_{li}} \in \{0,1\}, \quad i = 1 \dots I, \quad l = 1 \dots L;$$

$$Y_{il} = \begin{cases} 1, & \text{if there are 2 or more vehicles in station } l \text{ in shift } i \\ 0, & \text{otherwise} \end{cases}$$

$$\text{with:} \quad Y_{il} \in \{0,1\}, \quad i = 1 \dots I, \quad l = 1 \dots L;$$

The parameters are:

$$S_{lk} = \begin{cases} 1, & \text{if station } l \text{ can serve neighbour } k \text{ in less than 9 minutes} \\ 0, & \text{otherwise} \end{cases}$$

$$\text{with:} \quad S_{lk} \in \{0,1\}, \quad l = 1 \dots L, \quad k = 1 \dots K;$$

$$P_{kb} = \begin{cases} 1, & \text{if neighbor } k \text{ belongs to borough } b \\ 0, & \text{otherwise} \end{cases}$$

$$\text{with:} \quad P_{kb} \in \{0,1\}, \quad k = 1 \dots K, \quad b = 1 \dots B;$$

β_{ijk}: estimated demand of vehicle type j in neighbour k in shift i, where:

$$\beta_{ijk} = \lceil (\frac{N_{ijk}}{\sum_k N_{ijk}} \cdot M_j) \rceil$$

with:

M_j : Total number of vehicles of type j;

N_{ijk} : Total number of vehicles of type j used in shift i for neighborhood k in the historical data;

$C_{H_{li}}$: cost of putting the Hazmat in station l in shift i, where:

$$C_{H_{li}} = \frac{(\sum_k D_{lk} * \frac{1}{\beta_{ijk}}) - min(C_{H_{li}})}{max(C_{H_{li}}) - min(C_{H_{li}})};$$

$C_{S_{li}}$: cost of putting a Squad in station l in shift i;

$C_{R_{li}}$: cost of putting a Rescue in station l in shift i;

D_{lk}: distance from station l to neighbour k in seconds;

T_j: maximum number of vehicles of type j to allocate;

E_k: 1 if neighbourhood k has a station closer than 9 minutes, 0 otherwise;

B. Objective function

$$\begin{aligned} &\textit{Minimize } Z: \\ &\frac{\sum_i^I \sum_{j \in \{engine, ladder\}} \sum_k^K \left(B_{i,j,k} - \sum_l^L x_{i,j,k,l} \right)}{max(\sum_i^I \sum_{j \in \{engine, ladder\}} \sum_k^K B_{i,j,k} - \sum_l^L x_{i,j,k,l})} + \\ &+ \sum_i^I \sum_l^L C_{H_{l,i}} * Y_{H_{l,i}} + \sum_i^I \sum_l^L C_{S_{l,i}} * Y_{S_{l,i}} + \\ &+ \sum_i^I \sum_l^L C_{R_{l,i}} * Y_{R_{l,i}} + \frac{\sum_{l1,l2 \in \{L\}} N_{d->n,l1,l2}}{max(\sum_{l1,l2 \in \{L\}} N_{d->n,l1,l2})} + \\ &+ \frac{\sum_{l1,l2 \in \{L\}} N_{n->d,l1,l2}}{max(\sum_{l1,l2 \in \{L\}} N_{n->d,l1,l2})}; \end{aligned} \quad (1)$$

C. Constraints

$$[limit]\ \sum_{l}^{L} X_{ijkl} \leq \beta_{ijk}, \quad i=1\dots I, \quad j=1\dots J, \quad k=1\dots K; \tag{2}$$

$$[hazmat]\ \sum_{l}^{L} Y_{H_{li}} = T_{HAZMAT}, \quad i=1\dots I \tag{3}$$

$$[squads]\ \sum_{l}^{L} Y_{S_{li}} = T_{SQUADS}, \quad i=1\dots I \tag{4}$$

$$[rescue]\ \sum_{l}^{L} Y_{R_{li}} = T_{RESCUES}, \quad i=1\dots I \tag{5}$$

$$[rest\_vehicles]\ \sum_{k}^{K}\sum_{l}^{L} X_{ijkl} \leq T_j, \quad j \in \{engine, ladder\} \tag{6}$$

$$[9\_minute]\ \sum_{j}^{J}\sum_{l}^{L} X_{ijkl} * S_{kl} + \sum_{l}^{L}(Y_{H_{li}} + Y_{S_{li}} + Y_{R_{li}}) * S_{kl} \geq E_k, \quad i=1\dots I, \quad k=1\dots K; \tag{7}$$

$[station\_capacity]$

$$\sum_{j}^{J}\sum_{k}^{K} X_{ijkl} + Y_{H_{li}} + Y_{S_{li}} + Y_{R_{li}} \leq C_l, \quad i=1\dots I, \quad l=1\dots L; \tag{8}$$

$$[displacement\_night]\ \sum_{j}^{J}\sum_{k}^{K} X_{2,j,k,l} + Yh_{l,2} + Ys_{l,2} + Yr_{l,2} = \sum_{j}^{J}\sum_{k}^{K} X_{1,j,k,l} + Yh_{l,1} + Ys_{l,1} + Yr_{l,1} + \sum_{l_2}^{L}(N_{d->n,l_2,l} - N_{d->n,l,l_2}), \quad l=1\dots L; \tag{9}$$

$$[displacement\_day]\ \sum_{j}^{J}\sum_{k}^{K} X_{1,j,k,l} + Yh_{l,1} + Ys_{l,1} + Yr_{l,1} = \sum_{j}^{J}\sum_{k}^{K} X_{2,j,k,l} + Yh_{l,2} + Ys_{l,2} + Yr_{l,2} + \sum_{l_2}^{L}(N_{n->d,l_2,l} - N_{n->d,l,l_2}), \quad l=1\dots L; \tag{10}$$

$[more\_than\_one]$

$$2Y_{i,l} \leq \sum_{j}^{J}\sum_{k}^{K} X_{i,j,k,l} + Yh_{li} + Ys_{li} + Yr_{li} \leq C_l Y_{il} + 1, \quad i=1\dots I, l=1\dots L; \tag{11}$$

$[not\_just\_one\_type]$

$$\sum_{k}^{K} X_{i,j,k,l} \leq \sum_{j_2}^{J}\sum_{k}^{K} X_{i,j_2,k,l} + Y_{H_{li}} + Y_{S_{li}} + Y_{R_{li}} - Y_{li}, \quad i=1\dots I, \quad j=1\dots J, \quad l=1\dots L; \tag{12}$$

$[fair\_distribution]$

$$\sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K}\sum_{l}^{L} X_{i,j,k,l} * P_{k,b} \leq 0.3 * \sum_{i}^{I}\sum_{j}^{J}\sum_{k}^{K}\sum_{l}^{L} X_{i,j,k,l}, \quad b=1\dots B; \tag{13}$$

$[fair\_distribution\_scarce]$

$$\sum_{k}^{K}\sum_{l}^{L} S_{kl} * P_{kb} * Y_{jil} \geq 1, \quad b=1\dots B, i=1\dots I, j=1 \in \{S,R\}; \tag{14}$$

Objective (1) aims to minimize the total cost, combining different aspect making use of scalarization (with normalization) as [4], which includes: A) The sum of the demands for engines and ladder trucks across all neighbours and shifts, B) The costs associated with placing a hazmat, squad, and rescue vehicles at certain stations during each shift, and C) The number of vehicle movements between stations during shift changes. The goal is to find the allocation of vehicles that minimizes this sum while satisfying all the constraints. This would result in an efficient and equitable distribution of emergency service vehicles across New York City's fire stations. Constraint (2) ensures that the number of vehicles of type j assigned to serve neighborhood k during shift i does not exceed the estimated demand. Constraints (3)(4)(5) ensure that the exact amount of available scarce vehicles (hazmat, squads, and rescues) are assigned across all stations for each shift, while constraint (6) ensures that the rest of the vehicles do not exceed the total available for each type. Constraint (7) ensures that each neighborhood k is served by at least one vehicle within 9 minutes during shift i, given that there is a station able to do so, according to [1]. Constraint (8) restricts the total number of vehicles at station l during shift i according to its capacity. Constraints (9) and (10) ensure that the change in the number of vehicles at each station in the shift change match the vehicle movements. Constraint (11) aims to link the binary variable with its meaning. Constraint (12) avoid the possibility of having just one type of vehicle in a station which has more than one vehicle. Constraint (13) ensures that no borough in assigned more than 30% of the total amount of vehicles. And finally, constraint (14) ensures that there is at least one squad and one rescue in each borough during each shift.

IV. Implementation Details

This section is going to briefly explain the structure we have followed in our project's code. The main python script is called 'resolucion.ipynb'. In this notebook we have all the code to build the constraints, variables, the objective function and also processing the data we have extracted from different sources. This notebook contains all the information commented about the definitions of everything that has been needed. In conclusion, this notebook contains the parts of the code where the constraint, parameters, variables and objective function is defined.

On the other hand we have two folders in that zip. The first one is the 'aux-data' where we have all the csv files needed, that we created beforehand, to create all the parameters that we use.

Lastly we have 'functions' folder where we have different scripts to compute different parameters we knew we will need during the project. As we have said, this folder contains the scripts that have created the csv files of 'aux-data' folder.

Additionaly we have two notebooks that are really interesting, the first one is the 'time-complexity-analysis.ipynb' where we do all the code again for both solvers to get a dataframe in order to compare both in a plot, and also we perform 'Wilcoxon' independence test. Then we have the 'comparations-time.ipynb' where we have the plot of both performances.

V. Experiments

In this part of our project development, we proceeded to study the performance of the different solvers available through the OR-Tools API. Considering the nature of our model and problem, only solvers SCIP and CBC in their Mixed Integer Programming variant will be taken on board in this experimentation phase. As it can be seen in Figure 1, consistently the CBC solver has a shorter response time, converging to the optimal solution faster. The same way, as Table I highlights, SCIP (red line) is more inconsistent in comparison to the second solver considered (CBC, blue line), as some oscillations can be seen in time taken by the solver along the 30 iterations tested for each. To test if the differences in time between solvers that the graph expresses are actually significant, we employ a Wilcoxon test with a level of confidence of 95% because it is non-parametric and does not need us to make certain assumptions about time distributions. As the test's *p-value* reveals ($1.734 * 10^{-6}$), the difference in time to convergence between solvers is significant.

Solver	Average Time 2	Std. Time
CBC	5.4282	0.4257
SCIP	31.3144	4.2719

TABLE I: Solvers Comparison

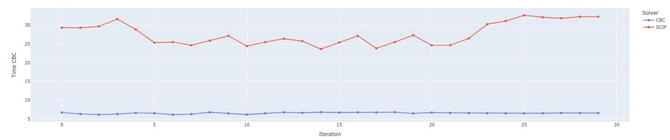

Fig. 1: Time Comparison between Solvers

VI. Conclusions

Our model of this allocation problem has an optimal solution reached by both of the solvers employed, which, once translated to the objective function gives a score of 1.91. Considering that we have up to 6 terms in the objective function, and that the maximum value of each of them could be 1 (as a result of the *Min-Max* scaling procedure applied to the first and last two terms, and because of the standardization of the costs associated to the allocation hazmat, rescue and squads vehicles) it represents a satisfactory result.
Once having described the value of our solution, let's have a detailed look at the actual distribution of vehicles that our model estimates as optimal. On the one hand, considering the ladder and engine vehicles, as Figures 2 and 3 reflect, the distribution of vehicles is quite uniform from a visual point of view, ensuring a considerable level of equity, as there is no borough which is isolated in terms of these two resources. In fact, focusing on the red landmarks, representing those stations where ladder or engine units can be found in both working shifts, are majorly equally distributed throughout the city. Nevertheless, for certain shifts, as we took into consideration when certain incidents were more likely to happen in determined zones, there are still some movements between stations.

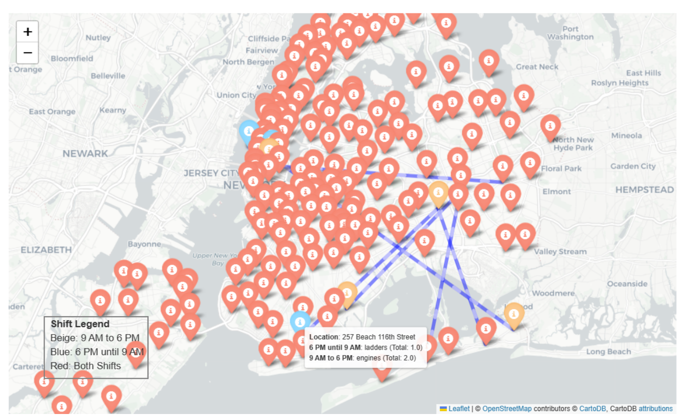

Fig. 2: Map representation of the distribution of Engines and Ladders

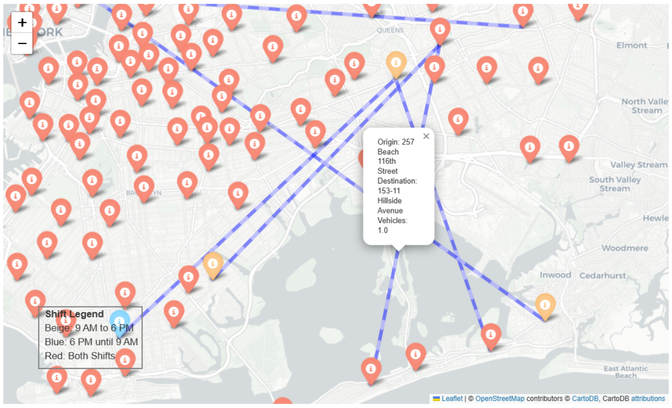

Fig. 3: Map representation of the transportation routes during shift change

This aspect is reflected on those stations which coloured in yellow or blue, representing stations where vehicles can only be found in one of the shifts, from 9 AM to 6 PM for the beige points and from 6 PM to 9 AM for the blue stations. In this sense, it is remarkable to underline how the vehicles rotate between this stations. We can see that the most common behaviour is to see movements from more 'isolated' stations, like the ones in Queens, to more populated and transited like Manhattan. This happens in the change of shift change from morning to night period. This might be revealing that the model has understood through our data that more populated zones are more likely to be more conflicting at night.

Moreover, the vehicle types with less availability –rescue, hazmart and, squad— have been deployed homogeneously among the NY city, as can be seen in Figure 4 and 5, shift from 9 AM to 6 PM and 6 PM to 9 AM, respectively.

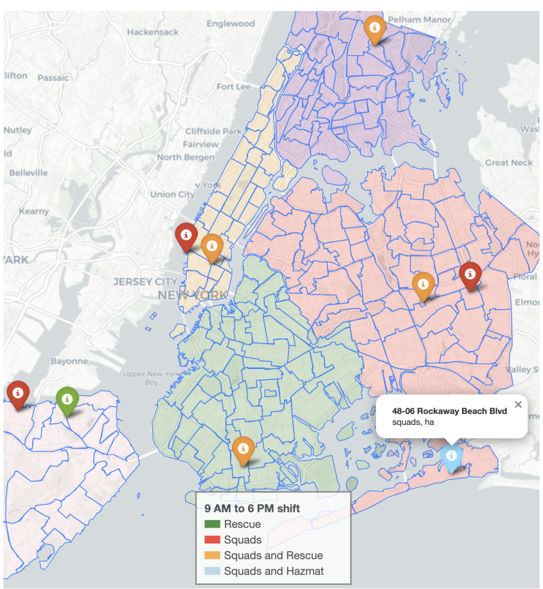

Fig. 4: Map representation of the distribution of Squads, Hazmats and Rescues across all the stations in shift 9 AM to 6 PM.

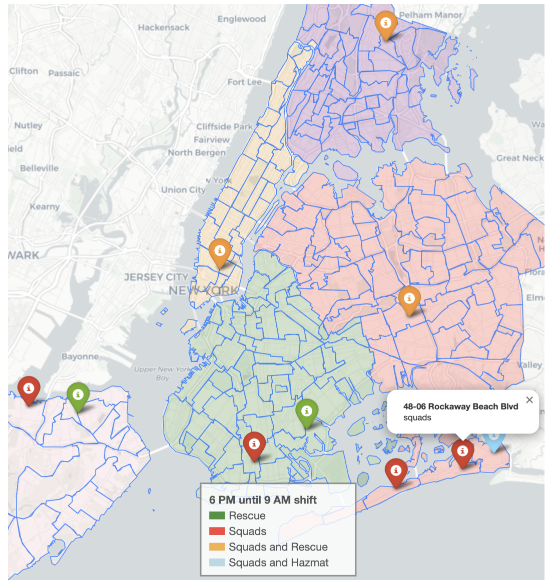

Fig. 5: Map representation of the distribution of Squads, Hazmats and Rescues across all the stations in shift 6 PM to 9 AM.

VII. Future work

Right now we do not have traffic conditions data available, even though it has a big influence in the time spent to arrive at the emergency. We could study peak hours and off-peak hours and we could improve the allocation of the vehicles in the neighborhoods.

Other aspect we could contemplate is using multi objective functions to see the variations in the results. As the syllabus of the course is just simple objective functions we did not have enough time to test it.

References

[1] A. T. Murray, "Optimising the spatial location of Urban Fire Stations," Fire Safety Journal, vol. 62, pp. 64–71, 2013. doi:10.1016/j.firesaf.2013.03.002

[2] L. Zhen, K. Wang, H. Hu, and D. Chang, "A simulation optimization framework for ambulance deployment and relocation problems," Computers & Industrial Engineering, vol. 72, pp. 12–23, 2014. doi:10.1016/j.cie.2014.03.008

[3] Jing Yao, Xiaoxiang Zhang, Alan T. Murray, "Location optimization of urban fire stations: Access and service coverage", Computers, Environment and Urban Systems, vol 73, pp. 184-190, 2019. doi.org/10.1016/j.compenvurbsys.2018.10.006.

[4] Nyoman Gunantara, "A review of multi-objective optimization: Methods and its applications", Cogent Engineering, vol 5, pp. 184-190, 2018. doi.org/10.1080/23311916.2018.1502242.

[5] Liu, Han, Soleimaniamiri, Saeid, Li, Xiaopeng, and Xie, Siyang, "Joint location and assignment optimization of multi-type fire vehicles", Computer-Aided Civil and Infrastructure Engineering, vol. 37, no. 8, pp. 976-990, 2022. https://doi.org/10.1111/mice.12774.

[6] Jian Wang, Han Liu, Shi An, and Na Cui, "A new partial coverage locating model for cooperative fire services", Information Sciences, vol. 373, pp. 527-538, 2016. https://doi.org/10.1016/j.ins.2016.06.030.

[7] National Fire Protection Association (NFPA) NFPA 1710: Standard for the Organization and Deployment of Fire Suppression Operations, Emergency Medical Operations, and Special Operations to the Public by Career Fire Departments, 2010. ⟨http://www.nfpa.org/⟩.