Machine Learning for predicting firefighters' interventions per type of mission

Roxane Elias Mallouhy[1], Christophe Guyeux[2], Chady Abou Jaoude[3], and Abdallah Makhoul[2]

[1] Prince Mohammad Bin Fahd University, Khobar, Kingdom of Saudi Arabia.
reliasmallouhy@pmu.edu.sa,
[2] University of Bourgogne Franche-Comté, Belfort,France.
christophe.guyeux@univ-fcomte.fr,
abdallah.makhoul@univ-fcomte.fr,
[3] Antonine University, Baabda, Lebanon. chady.aboujaoude@ua.edu.lb

Abstract. Fire brigades operations vary with time, climate, season, occasions, etc. For example, the frequency of accidents is greater during the day than at night. Thus, adjusting the need to the demand of fire departments by categories of operations leads to a reduction of material, financial and human resources, which can be very helpful during the financial and economic crisis most countries face. It also helps firefighters to be well prepared by knowing the type and number of human resources needed for the next operation. The aim of this study is to predict the number of firefighters interventions of 14 different categories: childbirth, drowning wasp, brawl, fire on public road, suicide, flood, accident on public road, traffic accident, witness, heating, fire, aid for people, emergency help for people. The experiments in this study on the dataset provided by the fire and rescue service, SDIS 25, in the Doubs-France region showed that it is not necessary to improve the prediction when more explanatory variables are added. Some characteristics are not informative and may reduce the accuracy of the results.

Keywords: prediction, firefighters, feature selection, breakpoint, anomalies detection, COVID-19

1 Introduction

1.1 Background

French firefighters are not only called to put out fires. Their mission goes beyond that. They are well trained and equipped to be the first responders to both medical and domestic emergencies. Due to the aging of the population and the restructuring of hospitals, firefighters are increasingly called to medical-social missions, especially as private paramedics. In fact, 80% of the activity of firefighters today is devoted to missions that are mainly not their responsibility [1]. At the end of 2020, there are about 251900 firefighters who have performed

4290700 missions in fires, emergency human assistance, traffic accidents and other miscellaneous missions [3]. Among them 78.25% were volunteer, 16.59% were professional and 5.16% were military firefighters [2].

The French health care system is considered one of the best in the world, but in recent years it has experienced an unprecedented crisis in hospitals. Understaffing of doctors and nurses is due to budget cuts that result in intensive use of existing staff while the number of patients increases. Hospitals have a funding system where funds are allocated based on the number of patients. Hence, some have cut their budgets and others have ceased operations altogether. As a result, firefighters' interventions appear to have increased to make up for shortages at hospitals.

On the other hand, fire brigades in France have been responsible for transporting patients from the hospital to their homes during this crisis. Their duties were extensive in this regard, as the aging population in France requires additional care and support. Budget cuts in hospitals have made it necessary to get people back home as quickly as possible, as the number of beds is saturated. This was the main task of the firefighters.

1.2 Importance

All of these and other factors have driven up the number of firefighters' missions: non-emergency calls have increased since 2009. The firefighters are on strike today, demanding from the Ministry of Interior a continuous increase in funding and better working conditions. Above all, they demand action for the public service, which has been neglected by the government [4]. Therefore, optimizing the use of their resources as needed will improve the efficiency of the response in terms of the number of personnel and latency during peak periods. This will also directly reduce financial resources.

It is important to emphasize that the influx of firefighters is somewhat related to climate, time, and some events. Floods in summer are an event that occurs less frequently than in winter. Or fires are more likely to occur in summer than in cold weather. Therefore, predicting such operations could be done using machine learning approaches, since fire department operations are directly related to human activities: accidents are more likely to occur during the day than at night or during a vacation. Therefore, the data used in this study particularly enable the use of time series forecasting in decision making by estimating future trends and scale.

1.3 Goals of this study

In this study, the predictions for the deployment process are made by type of deployment. A dataset of 14 categories of operations was provided by SDIS 25, the fire and rescue department in the Doubs-France region, and the prediction was made for each type. The data used is a set of observations collected in chronological order at even time intervals of one hour. Such a prediction indeed helps to sort the firefighters' missions and thus increase the efficiency of the response. Knowing the type of deployment could really help to competently prepare material and human resources. Moreover, such prediction is important for early identification of emergency operations that are vulnerable and high risk.

2 Related work

The use of machine learning is increasing every day and new techniques are being developed regularly. ML is used for everyday problems in various applications such as sentiment analysis, language modelling, text/image classification, object recognition, semantic segmentation, question answering, machine translation, speech recognition, time series analysis, and many others.
To boot, many researchers have explored machine learning techniques for modeling and optimizing emergency services. One notable study generated a distributed hourly volume of predictions using a Multilayer Perceptron and applied K-Means clustering. Heterogeneous spatial clusters were formed depending on the location and density of deployments. Results were compared with various ML techniques and found that their approach outperformed industry and time series forecasting methods at a precise spatial granularity level [5].
Another study aims to make a transition from traditional emergency records to an electronic nursing report to help the emergency department with both data analysis and clinical use by providing important information that can change the management of this department. K-fold cross-validation was used while training a multivariate logistic model. This method improved clinical care and quality assurance by integrating databases and registries [6].

On the other hand, a research attempted to place a fleet of ambulances at bases to increase the utility of the medical system's service level. An embedded simulator was integrated within a greedy allocation algorithm for a large Asian city and a significant result was demonstrated [7].
In addition, a study developed in [8] validated a deep-learning artificial intelligence algorithm to predict critical care needs during emergency medical services of a Korean national emergency department (ED) and outperformed prevailing triage tools and primitive warning scores. This was done by collecting information from 151 different ED in real time and authenticate run sheets from two different hospitals. To come to the point, countless works have been published to optimize or analyze the problems of health care and emergency department services using Artificial Intelligence and Machine Learning.

On the top of that, several research papers in the last three years have compassed the same topic as our study. Each of these works uses different investigation and algorithms to predict the number of firemen interventions and improve the response efficiency. In their work [?], Couchot et al. achieved accurate prediction for the number and type of fire responses in a geographic location while preserving the privacy of the victims whose lives were saved. They used k-anonymity and differential confidentiality-based approaches. Furthermore, Nahuis et al. in their study predicted the number of future firemen calls using the Long Short

Term Memory algorithm for the next one and three hours by collecting a sequential dataset over a 6-year period. They include in the data set various factors such as traffic, weather, holidays, sickness statistics, etc., and compare their results with the baseline as the average of the interventions [10]. Moreover, autoregression, moving average, autoregressive integrated moving average, and Prophet were implemented in [16] to achieve the same main goal of predicting firefighting operations.

Besides, Cerna et al. developed a machine learning approach to compute breakdowns and disruptions to improve the efficiency of firemen interventions over time [9]. Their goal was to detect breakdowns caused by the temporal state of human and vehicle equipment by implementing the LSTM method. Their results were compared with XGBoost, Adaptive Boosting (AdaBoost) and Gradient Boosting.

Also during the Covid 19 pandemic, the researchers considered this anomalous event and studied its impact on ambulance turnaround time, specifically that the number of resources in emeregency services was unsufficient during this situation. They implemented a multivariate model for both regular time series and irregular time series using Light Gradient Boosted Machine, Long Short-Term MemoryMultilayer Perceptron, and Prophet [15].

In addition, in their work, Héber et al. [11] on the one hand predicted the mortality of victims and the need for their transportation to medical facilities and on the other hand, aim to perturb the input data by applying k-anonymity and differential privacy techniques. This helps emergency services save more lives and avoid service interruptions. Along with, in [12] the number of fire brigades was predicted by region to optimize the placement of needed material and human resources at each site. First, they anonymized the location data by applying Differential Privacy, then they applied statistical estimators to reconstruct the dataset, and finally they used XGBoost to make predictions.

Furthermore, Héber et al. extended their research in [13] by predicting ambulance response time, which directly affects the quality of service provided. This was done by analyzing historical data and applying geo-indistinguishability to clean the data in terms of ambulance location.

3 Materials and Methods

3.1 Data collection

The SDIS 25 "Service Départemental d'Incendie et de Secours", i.e. the fire and rescue department in the Doubs region, France, provided us with the firefighters' interventions dataset. It contains abundant information about weather, vacations, climate, geographical location, curfew, etc. in the period from "01/01/2015 00:00:00" to "31/12/2020 23:00:00" in the form "DD/MM/YYY hh:mm:ss" with a block time of one hour. Eventually, the SDIS department started recording the interventions before 2015, but in this study, we limited the period to 5 years. Further details of the attributes can be found in [10, 17].

Withal, the Fire and Rescue Department provided not only a record of the number of interventions, but also another dataset that includes the type of interventions for each hour. In previous studies on the same topic, stated in the section 2 the datasets were conducted separately (number or type of interventions) and never combined, as was the case in this work. The dataset by intervention type draws on the same time period and step size as the dataset that carried out the number of interventions, but is much smaller. The number of attributes is limited to less context, including the reason/type of intervention. The comparison between the two datasets are shown in Table **??**. For ease of naming, we refer to the first dataset as the "dataset number" and the second dataset as the "dataset type".
It is also important to note that the "number dataset" has a unique line with the same index date, however the "type dataset" could have redundant indexes within the same date. This is because the first dataset indicates the number of interventions per day, while the second specifies the type of interventions per date, which may be different. For example, a possible scenario is to have 23 firemen operation on a given date and that these interventions are for different reasons and with different objectives, such as fire, accident, etc. So, as can be seen in table 1, there is a notable difference between the size of the two data sets in terms of attributes and rows.

	Dataset number	Dataset type
Duration	"01/01/2015 00:00:00" to "31/12/2020 23:00:00"	
Step period	1 hour	
Attributes size	1570	10
Rows size	52608	5886052

Table 1: Comparison between Dataset number and type

3.2 Dataset resampling and process

Working on the dataset by type of intervention, which has many categories on the same date, does not yield relevant information. Therefore, reassembling and reorganizing this dataset was the first modification to carried. We grouped the dataset by type of intervention (fire, delivery, etc.) and then created 14 sub-datasets for the different categories as demonstrated in Table 2. In the next phase, the following steps were performed:

1. "Datasets type" for each category were trained and tested using LightGBM [18] and XGBOOST [19]. These subsets contain only information about the 'year', the 'month', the 'number of days in the year', the 'days in the week' and the 'hour in the day'.
2. "Datasets type" were merged with "Dataset number" to test the efficiency of adding more explanatory variables for weather, climate, vacations, occasions, etc.

3. Since step 2 requires a lot of computation time, feature selection was applied using XGBOOST featureimportance technique to reduce the computation time.
4. The accuracy was checked after selecting the best features of the merged dataset.
5. Results were compared all together to draw a conclusion.

Category	Description	Dataset size
Childbirth	Labour/delivery	36905
Drown	Submerge/flood	39203
Wasp	Insect stings	55045
Brawl	Rough fight	66161
Fire on public road	In any public location	115604
Suicide	Dying intentionaly	157019
Water-flood	Water submerging	167880
Public road accident	Highway/train/bus...	732584
Traffic accident	Vehicles accidents	737529
Witness	Unconsciousness	738327
Heating	Arson, fire detected by smoke, etc...	924381
Fire	At home, bulduings, ...	1299319
Help for people	Any non-urgent mission	1556440
Emergency aid to people	Any urgent mission	2410564

Table 2: Datasets by category by size ascending order

3.3 Methodology

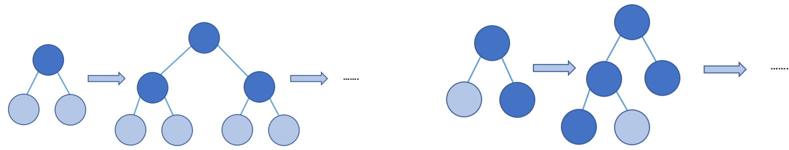
The "dataset type", containing 10 attributes and gathering all fire operations categories together, was used to obtain the subsets of data by mission of interventions, grouping each type separately. In this way, 14 new datasets were generated containing the date and the number of deployments of firefighters on each one-hour step for each specific mission. It should be cognizant that there may be some dates that are not included in the dataset. For example: on "2015-01-01" at "01:00:00" there were 7 firefighters on duty for the mission 'childbirth', and that two hours later, at "03:00:00", there were no more missions of birth delivery.

3.3.1 Training and testing for the 14 subdatasets

In this work, two of the most popular machine learning algorithms were used: eXtreme Gradient Boosting (XGBOOST) and Light Gradient Boosting Machine (LightGBM). XGBOOST, which is used for both classification and regression tasks, is a technique that follows the concept of level-wise growth (Figure 1(a)).

It is the improved Gradient Boosting Decision Tree algorithm [20] that considers an objective function to prevent over-fitting and can automatically use CPU for parallel multi-threaded computations to improve the speed and performance of the model. Similar to XGBOOST, LIGHTGBM also uses decision trees for classification and regression. However, it solves predictions for large datasets faster and requires less memory because it is an algorithm based on a tree leaf-wise growth strategy (Figure 1(b). Yet, this can lead to an over-fitted model.

Besides, Optuna [21], a hyperparameter optimization framework was applied to both algorithms to find the best parameters in XGBOOST (learning_rate, max_depth, random_state, n_estimators) and in LightGBM (learning_rate, max_depth, n_estimators, num_leaves, random_state). The values of each parameter were different for each category of firefighting operations because the dataset is completely different.



((a)) Level tree growth strategy ((b)) Leaf tree growth strategy

Fig. 1: Two different strategies of tree growth

3.3.2 Merging datasets

The combination of the two datasets "number" and "type" was an important process for data analysis to predict the number of fire calls. The approach was to merge the "type dataset" and the "number dataset" into a new one using the index column carrying the date/time information. If the date was missing from the "type dataset" because there was no deployment associated with that particular date/time, a row with zero interventions was attached. Adding this row was essential in this study to allow a fair and accurate comparison across all days for all approaches.

To perform this merging process, we first ensure that both datasets have the same size, i.e., the same date range. Second, we omitted the 'target' column from the "number dataset", which refers to the number of deployments, since the purpose is to predict the number of fire deployments per category. Therefore, the 'target' considered in the coming experiments is the one included in the 'type dataset'. We also verify that the format of the indexes is identical in both datasets. Table 3, Table 4 and Table 5 show a selection of the original dataset 'Fire', the type of dataset and the resulting dataset after the merging process respectively.

Date	target	Year	Month	Day in the year	Day in the week	Hour
1/5/2015 5:00	7	2015	1	5	0	5
1/5/2015 6:00	7	2015	1	5	0	6
1/5/2015 7:00	0	2015	1	5	0	7
1/5/2015 8:00	5	2015	1	5	0	8

Table 3: Fire Dataset sample for 4 consecutive hours

Date	rolling mean	current Weather_0	...	noon	night	daylight SavingTime
1/5/2015 5:00	-1.04268	0.230316	...	FALSE	TRUE	TRUE
1/5/2015 6:00	-0.8858	0.230316	...	FALSE	TRUE	TRUE
1/5/2015 7:00	-0.10139	0.230316	...	FALSE	TRUE	TRUE
1/5/2015 8:00	-0.10139	0.230316	...	FALSE	TRUE	TRUE

Table 4: A sample of the "Number Dataset"

Date	rolling mean	current Weather_0	daylight SavingTime	...	Month	Day in the year	Target
1/5/2015 6:00	-0.8858	0.230316	TRUE	...	1	5	7
1/5/2015 7:00	-0.10139	0.230316	TRUE	...	1	5	0
1/5/2015 8:00	-0.10139	0.230316	TRUE	...	1	5	5
1/5/2015 9:00	-0.41515	0.230316	TRUE	...	1	5	5

Table 5: Sample of the dataset after merging the Fire with the "Number Dataset"

3.3.3 Feature selection

The 14 merged datasets evidently contain a large number of attributes with 1570 attributes coming from the original "number dataset" and 6 more coming from the dataset of any category of intervention, i.e. a total of 1576 attributes.

These superimposed features require a lot of computation and training time. It took too many resources and is actually not convincing. Many attributes are irrelevant and their presence in the dataset does not play a positive role in prediction. The opposite is true: when the number of variables is significantly high, the accuracy of prediction decreases.

Therefore, in this work, the selection of a reduced number of attributes is desirable for practical reasons. To achieve this goal, the technique of feature importance with gradient boosting was applied, in which an importance score is calculated for each attribute, allowing them to be ranked and compared. For each of the 14 available datasets, the minimum number of features giving the best Mean Absolute Error and Root Mean Squared Error was chosen.

4 Experimental results and interpretations

After processing the data and then merging them into datasets for each category of fire operations, and after reducing the size of the large datum by selecting the minimum number of characteristics that yield the best accuracy for the statistical features MAE and RMSE, the next phase was to make predictions and test the accuracy and errors for different approaches. For all experiments, the dataset was divided into train, validation, and test, with an early stop round of 20 for XGBOOST with a "poisson" objective function and 500 for LightGBM with a "gbdt" boosting type.
Briefly, three major experiments were conducted in this study and statistical characteristics were calculated in each.

- Original datasets of the 14 different categories containing only the 5 attributes (year, month, number of days in the year, days in the numbers, and hour in the day).
- 14 datasets after merging the "type dataset" with the "number dataset", deriving a huge datum of 1576 attributes.
- 14 datasets after selecting the best attributes that provide the highest accuracy.

MAE and RMSE were calculated for both XGBoost and LightGBM (Table 7), with the exception that after merging both datasets without feature selection, the experiment was performed only with XGBOOST because of the enormous computation time (Table 6).

As might be expected, feature selection resulted in a reduction in MAE and RMSE for most categories of the datasets. This explains that this technique is feasible and gives good prediction results, as shown in Table 7. Nevertheless, this need not be the case when forecasting a simple dataset containing only time and date attributes, as shown in Table 6. Dealing with complex and large data sets increases variability and thus the error rate.
Furthermore, comparing the statistical features of XGBOOSt and LIGHTGBM, it is conspicuous to state that LightGBM has the lowest MAE and RMSE. It is obvious that LightGBM is faster than XGboost, especially when the data is very large similar to this study.

Over and above that, the nature of the dataset played a major role in predictive accuracy. In fact, the 14 data sets vary greatly in size, ranging from 36905 to 2410564, which is about 65 times larger than the dataset for the childbirth. Furthermore, not only did size play a large role in the error rate, but also the category of the data set. Floods, fires, accidents, and many other fire incidents are

2*Dataset	Without feature selection	
	MAE	RMSE
Childbirth	0.689	1.795
Drown	0.302	2.89
Wasp	0.653	1.835
Brawl	1.375	2.669
Fire on public road	2.244	4.376
Suicide	2.507	5.203
Water-flood	2.061	4.35
Public road accident	9.935	14.958
Traffic accident	9.869	14.874
Witness	7.506	11.852
Heating	7.421	23.19
Fire	10.305	23.054
Help for people	11.256	16.545
Emergency aid to people	12.145	16.669

Table 6: MAE and RMSE after combining the datasets and before feature selection

	Before merging the datasets				After Feature Selection			
2*Dataset	XGBOOST		LightGBM		XGBOOST		LightGBM	
	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Childbirth	0.479	1.523	0.632	1.452	0.434	1.611	0.403	1.263
Drown	0.118	2.453	0.327	2.327	0.223	3.244	0.206	2.68
Wasp	0.322	1.313	0.471	1.332	0.417	1.851	0.403	1.274
Brawl	0.865	2.221	1.263	2.437	1.398	2.915	1.452	2.725
Fire on public road	1.577	3.688	2.049	4.042	1.509	4.911	0.926	3.186
Suicide	1.491	3.464	2.465	4.367	2.302	4.708	1.096	3.469
Water-flood	1.331	3.731	1.445	3.487	1.589	4.487	1.085	3.235
Public road accident	5.503	13.307	6.721	11.37	6.382	11.719	3.505	8.893
Traffic accident	5.406	10.689	6.348	11.029	6.567	11.806	3.332	9.423
Witness	3.967	6.402	4.775	6.932	4.292	6.76	2.258	5.64
Heating	3.247	10.546	3.507	9.485	4.14	16.908	4.768	17.234
Fire	4.435	14.07	4.848	11.374	4.93	22.406	5.036	28.863
Help for people	5.973	9.812	6.934	10.177	5.792	9.828	3.225	8.144
Emergency aid to people	6.914	11.85	8.772	12.846	8.087	13.43	4.227	10.864

Table 7: MAE and RMSE for ”Type datasets”

somehow related to time and date, i.e., seasonality. However, some other types of dataset, e.g. , child births, wasps, etc., are not so easy to predict because the frequency of occurrence is not known as a function of season or time.

5 Conclusion

In this work, an improvement of previous studies was achieved by merging the two datasets on the number of firemen internevtions and the type of missions provided by the Department of Fire and Rescue SDIS 25 in Doubs, France, in order to investigate the effect of adding explanatory variables to the existing attributes, which are considered very simple and refer only to the date and time. The datasets for each category were prepared by grouping the deployment types and creating 14 sub-datasets for each fire deployment independently. Afterwards, these datasets were merged with the huge original data used in previous researches, and finally, the best features for each sub-dataset were selected using the feature importance technique to reduce computation time and storage requirements. All the assessments were performed using two well-known boosting machine learning algorithms XGBoost and LightGBM.
The results demonstrated good accuracy when processing the 14 sub-datasets of different categories without adding explanatory variables or feature selection. On the other hand, comparing the accuracy before and after feature selection, the errors were lower after the number of attributes was reduced, but never better than the original 14 sub-datasets before any change.

Future work is absolutely necessary for this firemen dataset to improve the accuracy of forecasting operations. Expanding the dataset to include more regions and applying clustering techniques by population size, age, education level, etc. may be a coming plan.

Acknowledgement

This work has been supported by the EIPHI Graduate School (contract ANR-17-EURE-0002) and is partially funded with support from the Hubert Curien CEDRE programme n° 46543ZD.

References

1. France Bleu. (2019). Trop d'interventions de secours aux personnes : les pompiers du Calvados en appellent au Premier ministre. [online] Available at: https://www.francebleu.fr/infos/societe/trop-d-interventions-de-secours-aux-personnes-les-pompiers-du-calvados-en-appellent-au-1er-ministre-1574089455.
2. DMASP. (2021). Les pompier en chiffres en 2020. [online] Available at: https://www.dmasp.fr/les-pompier-en-chiffres-en-2020/ [Accessed 23 Jan. 2022].
3. l'Intérieur, M., 2022. 2020. [online] https://mobile.interieur.gouv.fr/Publications/Statistiques/Securite-civile/2020. Available at: ¡https://mobile.interieur.gouv.fr/Publications/Statistiques/Securite-civile/2020¿ [Accessed 20 January 2022].
4. www.epsu.org. (n.d.). French firefighters demand more staffing, higher pay, and better possibilities for career development — EPSU. [online] Available at: https://www.epsu.org/article/french-firefighters-demand-more-staffing-higher-pay-and-better-possibilities-career [Accessed 23 Jan. 2022].

5. Martin, R.J., Mousavi, R. and Saydam, C., 2021. Predicting emergency medical service call demand: A modern spatiotemporal machine learning approach. Operations Research for Health Care, 28, p.100285.
6. Redfield, C., Tlimat, A., Halpern, Y., Schoenfeld, D.W., Ullman, E., Sontag, D.A., Nathanson, L.A. and Horng, S., 2020. Derivation and validation of a machine learning record linkage algorithm between emergency medical services and the emergency department. Journal of the American Medical Informatics Association, 27(1), pp.147-153.
7. Yue, Y., Marla, L. and Krishnan, R., 2012, July. An efficient simulation-based approach to ambulance fleet allocation and dynamic redeployment. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 26, No. 1).
8. Kang, D.Y., Cho, K.J., Kwon, O., Kwon, J.M., Jeon, K.H., Park, H., Lee, Y., Park, J. and Oh, B.H., 2020. Artificial intelligence algorithm to predict the need for critical care in prehospital emergency medical services. Scandinavian journal of trauma, resuscitation and emergency medicine, 28(1), pp.1-8.
9. Cerna, S., Guyeux, C., Royer, G., Chevallier, C. and Plumerel, G., 2020. Predicting fire brigades operational breakdowns: A real case study. Mathematics, 8(8), p.1383.
10. Nahuis, S.L.C., Guyeux, C., Arcolezi, H.H., Couturier, R., Royer, G. and Lotufo, A.D.P., 2019, April. Long short-term memory for predicting firemen interventions. In 2019 6th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 1132-1137). Ieee.
11. Arcolezi, H.H., Cerna, S., Couchot, J.F., Guyeux, C. and Makhoul, A., 2021. Privacy-Preserving Prediction of Victim's Mortality and Their Need for Transportation to Health Facilities. IEEE Transactions on Industrial Informatics.
12. Arcolezi, H.H., Couchot, J.F., Cerna, S., Guyeux, C., Royer, G., Al Bouna, B. and Xiao, X., 2020. Forecasting the number of firefighter interventions per region with local-differential-privacy-based data. Computers Security, 96, p.101888.
13. Arcolezi, H.H., Cerna, S., Guyeux, C. and Couchot, J.F., 2021. Preserving geo-indistinguishability of the emergency scene to predict ambulance response time. Mathematical and Computational Applications, 26(3), p.56.
14. Couchot, J.F., Guyeux, C. and Royer, G., 2019, June. Anonymously forecasting the number and nature of firefighting operations. In Proceedings of the 23rd International Database Applications Engineering Symposium (pp. 1-8).
15. Cerna, S., Arcolezi, H.H., Guyeux, C., Royer-Fey, G. and Chevallier, C., 2021. Machine learning-based forecasting of firemen ambulances' turnaround time in hospitals, considering the COVID-19 impact. Applied Soft Computing, p.107561.
16. Elias Mallouhy, R., Guyeux, C., Abou Jaoude, C. and Makhoul, A., 2021, May. Time Series Forecasting for the Number of Firefighters Interventions. In International Conference on Advanced Information Networking and Applications (pp. 39-50). Springer, Cham.
17. Couchot, J.F., Guyeux, C. and Royer, G., 2019, June. Anonymously forecasting the number and nature of firefighting operations. In Proceedings of the 23rd International Database Applications Engineering Symposium (pp. 1-8).
18. Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q. and Liu, T.Y., 2017. Lightgbm: A highly efficient gradient boosting decision tree. Advances in neural information processing systems, 30.
19. Chen, T. and Guestrin, C., 2016, August. Xgboost: A scalable tree boosting system. In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining (pp. 785-794).
20. Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Annals of statistics, pp.1189-1232.

21. Akiba, T., Sano, S., Yanase, T., Ohta, T. and Koyama, M., 2019, July. Optuna: A next-generation hyperparameter optimization framework. In