Time Series Forecasting for the Number of Firefighters Interventions

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Abstract Time series forecasting is one of the most attractive analysis of dataset that involves a time component to extract meaningful results in economy, biology, meteorology, civil protection services, retail, etc. This paper aims to study three different time series forecasting algorithms and compare them to other models applied in previous researchers' work as well as an application of Prophet tool launched by Facebook. This work relies on an hourly real dataset of firefighters' interventions registered from 2006 till 2017 in the region of Doubs-France by the fire and rescue department. Each algorithm is explained with best fit parameters, statistical features are calculated and then compared between applied models on the same dataset.

1 Introduction

Many studies show that reaching good forecasts is vital in many activities such as industries, commerce, economy, and science. The fact of gathering a collection of observations over time will provide predictions of new observations in the future and extract meaningful characteristics of the data and statistics in different time intervals: hours, days, weeks, months, and years. The usage of data science, machine learning, and time series forecasting are feasible in the prediction of firefighters' interventions since it is logical to assume that firefighters' interventions are affected somehow by temporal, climatic, and other events such as new year's eve, snowing weather, traffic peak time, fires in summer, holidays, etc. Due to the French economic crisis (closure of small hospitals, population growth, etc.), the impact of optimizing the number of human interventions leads directly to a reduction and better control in the financial, human, and material resources. The goal is to

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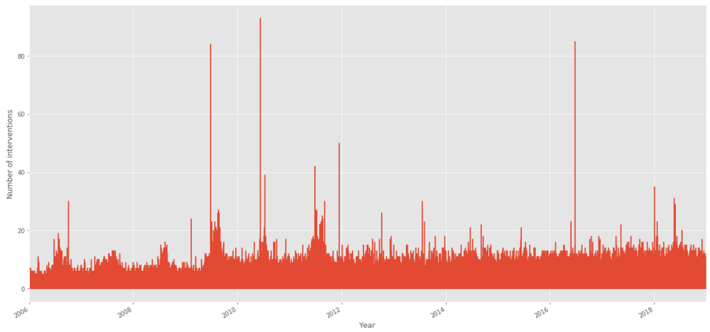


Fig. 1 Number of firefighter interventions from 2006 until 2017.

size the number of firefighters according to the need and demand: a greater number of firefighters should be available when they are mostly used. Indeed, the number of guards available should be related to the location, number, and type of the intervention. For example, during the weekend when accidents indeed increase, the number of firefighters ready to serve the society should be greater than a regular working weekday where most of the people reside in their offices. A trusted result and high prediction are affected by many factors: the algorithm used to train and test the dataset plays a big role as well as the chosen parameters. In this work, three different well-known time series algorithms have been implemented: Auto Regression (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA). Each algorithm is explained and detailed in Section 3. The dataset used carries information about firefighters' interventions in the region of Doubs-France from 01/01/2006 00:00:00" until 31/12/2017 23:00:00". All the data were registered by the fire and rescue department SDIS 25 by blocks of one hour [23]. An overview of the number of firefighters interventions through the years is shown in Figure 1.

This paper concentrates on statistical parameters calculated of three different Machine Learning algorithms to predict the number of firefighters' interventions, prophet, and comparison between the applied algorithms and related work using the same dataset.The remaining of this paper is structured as follows: literature review providing an overview about related work done by researchers on the same topic; Machine Learning algorithms for predicting firefighters' interventions explaining the three ML models used; parameters chosen showing the values used for the corresponding algorithms; building data with Prophet by applying this Facebook tool on the firefighters dataset; obtained results; results interpretation, and conclusion.

2 Literature Review

Many influential works on time series forecasting have been published in the latest years with enormous progress in this field. The idea of forecasting starts with

Gardner and Snyder who boost two subsequent papers in the same year (1985) in the area of time series forecasting about exponential smoothing methods. Gardner provided a review of all existing work done to that date and extended his research to include a damped trend [2] After Gardner's work, Snyder demonstrated that simple exponential smoothing could arise from state space model innovation [3]. Most of the researches since 1985 has focused on empirical properties [10], forecasts evaluations [9], and proposition of new methods for initialization and estimation [8]. Many studies have stimulated the use of exponential smoothing methods in various areas such as air passengers [16], computer components [5], and production planning [12]. Later on, numerous variations on original methods have been proposed to deal with continuities, constraints, and renormalization at each period time [15], [13]. Multivariate simple exponential smoothing was used for processing the control charts by introducing a moving average technique [21]. Moreover, Taylor [7] and Hyndman *et al.* [20] have extended basic methods and have included all 15 different exponential methods. Moreover, they have proposed models that correspond to multiplicative error cases and additive errors. However, these methods were not unique since it has been known that ARIMA models give equivalent results in forecasting, but the innovation in their work was that statistical models can lead to non-linear exponential smoothing methods.

Early studies of time series forecasting in the nineteenth century were globally based on the idea that every single time series can be seen as a realization of a stochastic process. Based on this simple proposal, many time series methods since then have been developed. Workers such as Walker, Yaglom, Slustsky and Yule [22] formulated the concept of moving average MA model and autoregressive AR models. The conception of linear forecasting happened by the decomposition theorem. After that, many studies have appeared dealing with parameter identification, forecasting estimation, and model checking. Time series forecasting in this paper is specifically studied by running a real dataset of firefighters' interventions. This area of research in machine learning is new some-how where only a few articles are targeting this topic. A work achieved by C. Guyeux *et al.* [24] started by collecting a list of interventions and preparing the set for learning, validating, and testing. Then, by using supercomputers, the learning was carried out on an ad hoc Multi-Layer Perception. The study ends up by applying the neural architecture on a real case study with mature and encouraging results. Another work done by Couchot *et al.* [23] has shown that a machine learning tool can provide accurate results by deploying a learning process based on real and anonymized data using extreme gradient boosting to guess an accurate behavior. Ñahuis *et al.* [26, 28], using the same firefighter's dataset demonstrated that machine learning is mature enough to make feasible predictions for critical events such as natural disasters. They used LSTM and XGBoost approaches to predict the number of firefighter's interventions. These investigations have been deepened following a feature-based machine learning approach in various directions [29, 25, 27], but never by considering the time series alone.

3 Machine Learning Algorithms for predicting firefighters' interventions

Introductory books on time-series algorithms and analysis include Davis and Brockwell [19], Diggle [4], Swift and Janacek [11], Wei, Ord and Kendall [6].

3.1 Auto-regressive model

Auto regression is a statistical time series model that predicts an output for the near-future (number of houses sold, price of something, number of interventions, ...) based on past values. It was originated in 1920 by Udny Yule, Eugen Slutsky, and Ragnar Frisch [14]. For instance, to predict today's value based on yesterday, last week, last month, or last year one. AR models are also called Markov models, conditional models, or transition ones. Regression uses external factors which are independent as an explanatory variable for the dependent values. Autoregression model is conditioned by the product of certain lagged variables and coefficients allowing inference to be made. In reality, AR works hardly if the future predictors are unknown because it requires a set of predictor variables. On the other hand, AR is capable of adjusting the regression coefficient β and violating the assumption of uncorrelated error since the independent observations are time lagged values for the dependent observations.

In an AR model, the value of the predicted outcome variable (Y) at some time t is $Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_t$ where the parameters $\beta_0 + \beta_1 Y_{t-1}$ rely on the past and ε_t which is the white noise could not be predictable from the past. It is important to mention that knowing the previous lagged values of Y_{t-2}, Y_{t-3} does not affect the prediction of Y_t because as shown in the formula, Y_t is affected only by Y_{t-1}.

3.2 Moving Average model

Moving Average MA is a model introduced in 1921 by Hooker who considers multiple period averages to predict future output and event [1]. It is an effective and naive technique in time series forecasting used for data prediction, data preparation or feature engineering. It uses the most recent historical data values to generate a forecast. MA removed the fine-grained variation between time steps, to expose the signal. This method uses the average data periods' number. The term "moving" indicates the up and down moves of the time series done to calculate the average of a fixed number of observations. On the other hand, the process of averaging relies on the overlapping observations that create averages. Moving Average method can be used for both linear and non-linear trends. However, it is not applicable for short time series forecasting fluctuation because the trend obtained by applying the model is neither a standard curve nor a straight line. Besides, trend values are not available for some intervals at the start and the end values of time series.

The outcome value in the MA(q) model, a moving average model of order q, is presented as the following:
$y_t = c + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2}+...+\theta_q\varepsilon_{t-q}$ where ε_t is the white noise. This technique involves creating a new time series with compromised values of row observations and average in the original data set time series. Moreover, it relies on past forecast errors.

3.3 AutoRegressive Integrated Moving Average

ARIMA, also called Box-Jenkins, is a model proposed by George Box and Gwilym Jenkins in 1970 by using a mathematical approach to describe changes in the time series forecasting [18]. ARIMA is an integration of auto regression and moving average methods that use a dependent relationship between an observation and some number of lagged observations by differencing between raw observations. It subtracts an observation from the previous time step and takes into consideration the residual error. ARIMA is a powerful model as it takes into consideration history as an explanatory variable, but in such model, the data cost is usually high due to the large observations requirement needed to build it properly. A standard notation for ARIMA being used is ARIMA (p,d,q) where:

- p: is the auto-regressive part of the model, which means the number of lag observations that are included in the model. It helps to incorporate the effect of past values of the model. In other terms, it is logical to state that it is likely to need 5 firefighters tomorrow if the number of interventions was 5 for the past 4 days. A stationary series with autocorrelation can be corrected by adding enough AutoRegression terms.
- d: is the integrated part of the model. It shows the degree of differencing the number of times that the raw observations have been differenced. This is similar to state that if in the last 4 days the difference in the number of interventions has been very small, it is likely to be the same tomorrow. The order of differencing required is the minimum order needed to get a near-stationary series.
- q: order of moving average which is the size of the MA window. Autocorrelation graph shows the error of the lagged forecast. The ACF shows the number of MA terms required to remove autocorrelation in the stationaries series.

4 Parameters chosen

Auto Regression algorithm does not need any parameters to be chosen or modified as explained in the formula in the previous section. Nevertheless, different parameters were tested and registered for Moving Average and ARIMA;

4.1 Window size for Moving Average

After trying different values of window sizes for different hours and days, the best size chosen is 3 hours having the minimal values of MAE and RMSE. On the other hand, to select the values of ARIMA, the following parameters should be taken into consideration:

1. p: the order of AR term was basically taken to be equal to the number of lags that crosses the significance limit in the Autocorrelation Figure 3a. It is observed that the ACF lag 4 is quite significant. Then, p was fixed to 4.
2. d: let us use the Augmented Dickey Fuller (ADF) test to see if the number of interventions is stationary. The p_value found is $5.12e^{-28}$, which is lower than the significant level of 0.05. This means that no differencing is needed. Let's fix d to 0.
3. q: one lag above the significance level was found, thus q=1 (Figure 3b).

Figure 2 shows the actual number of interventions versus the predicted ones after applying a moving average transformation overlaid by 3 hours.

Table 1 Different window sizes for Moving Average Algorithm.

Window Size	MAE
1 hour	1.477
2 hours	1.360
3 hours	1.349
4 hours	1.359
5 hours	1.387
10 hours	1.541

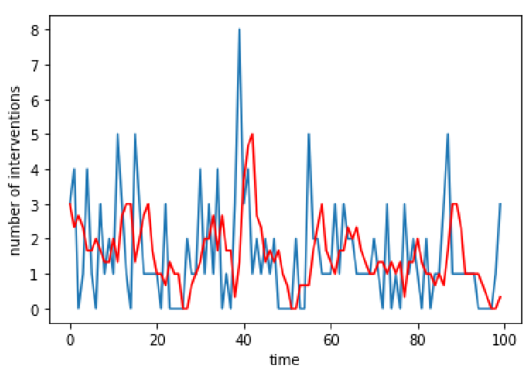
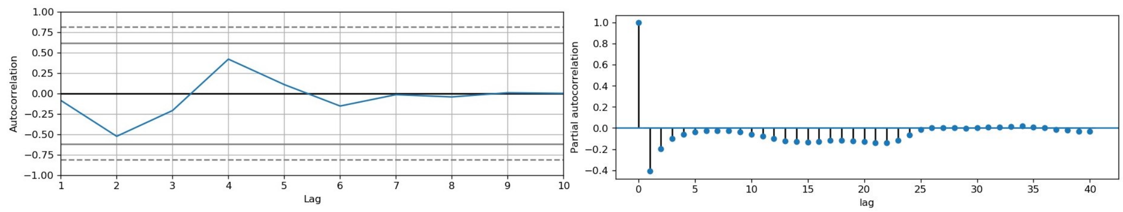


Fig. 2 Actual versus predicted number of interventions.

4.2 P, d and q parameters for ARIMA

After determining the values of p, d and q, ARIMA model is fitted by using order (4,0,1).



(a) Autocorrelation plot (b) Partial autocorrelation plot

Fig. 3 p and q parameters.

5 Building data with Prophet

A prophet forecasting model is an open-source algorithm designed by Facebook in 2017 [17] for time series having common features and intuitive parameters, where experts and non-experts in statistics and time series forecasting can use it. Prophet is based on time series models and relies on four main components: (1) Yearly and weekly seasonality, (2) Non linear trend, (3) Holidays and (4) Error. Prophet fits very well for data that have at least one year of historical inputs with daily periodicity. It is very fast in terms of fitting the model, working without converting data into time-series objects, and being robust to missing values. In addition, prophet is simpler compared to other time series forecasting algorithms, because it requires less number of parameters and models. Prophet works as following: $y(t) = g(t) + s(t) + h(t) + \varepsilon_t$ where:

- g(t): describes the increase or decrease trends in the long-term data.
- s(t): represents the impact of seasonal factors over the year on the time-series data.
- h(t): models how large events and holidays affect the data.
- ε_t: shows the non reducible error term.

For prophet's preparation, a new dataframe should be found: a new column is added to the data that emerges years, months, days, and hours. Then, this column is renamed to 'ds' and the predicted output presented in the data under the name of nbinterventions is renamed as 'y'. Figure 4 helps to visualize the forecast of the dataframe where the black dots display actual measurements, the blue line indicates Prophet's forecast and the light blue shaded line shows uncertainty intervals. It looks like the number of interventions was increasing over the years slightly.

Table 2 New dataframe for the dataset.

Index	y	ds
0	1	2006-01-01 00:00:00
1	1	2006-01-01 01:00:00
2	0	2006-01-01 02:00:00
3	2	2006-01-01 03:00:00
4	4	2006-01-01 04:00:00

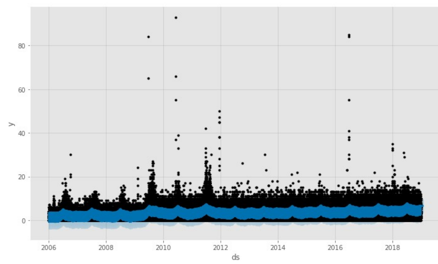


Fig. 4 Forecast for Prophet algorithm.

6 Obtained results

Considering having 24 hours per day, 7 days per week, 30 days per month, and 365 days per year, three algorithms have been implemented: AR, MA and ARIMA on the dataset in addition to the prophet. Statistical features of firemen predictions for every year from 2006 until 2017 have been registered in Table 4 and graphs that gather all statistical features are shown in Figure 5. On the other hand, let us overview the result of the forecast by illustrating a breakdown of the former elements (Figure 6) for daily, weekly and yearly trends using the prophet tool. The number of interventions during a trimmed time slot is shown in Figure 7 where:

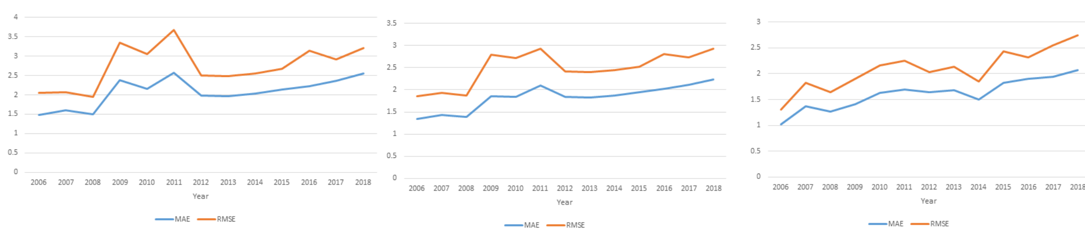
- yellow plot represents the actual number of interventions y.
- purple plot indicates the prediction yhat.
- blue and red plots show the upper and lower bound of prediction respectively.

Table 3 Statistical features using AutoRegression for different time slots.

Time	MAE	MSE	RMSE
1 hour	0.307	0.094	0.307
2 hours	0.403	0.171	0.414
12 hours	1.205	1.932	1.390
1 day	1.288	2.128	1.459
5 days	1.168	1.822	1.350
1 week	1.209	2.057	1.434
1 month	1.213	2.123	1.457

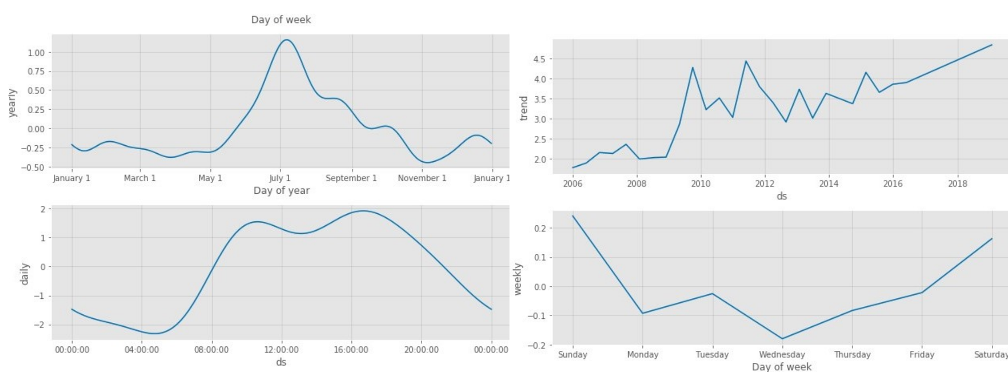
Table 4 Statistical features using AR,MA ,ARIMA and prophet from 2006 until 2017.

	AR		MA		ARIMA		Prophet	
2006	1.481	2.046	1.349	1.86	1.018	1.307	2.55	3.53
2007	1.601	2.064	1.429	1.924	1.376	1.822	1.95	2.97
2008	1.496	1.952	1.385	1.868	1.263	1.644	1.31	1.63
2009	2.374	3.35	1.854	2.787	1.414	1.904	3.25	5.69
2010	2.161	3.058	1.847	2.716	1.629	2.154	2.00	2.23
2011	2.574	3.676	2.09	2.922	1.699	2.247	6.00	11.00
2012	1.99	2.5	1.84	2.415	1.642	2.031	2.44	2.87
2013	1.972	2.478	1.83	2.392	1.682	2.14	2.33	2.66
2014	2.04	2.545	1.874	2.451	1.504	1.843	2.44	2.90
2015	2.145	2.678	1.939	2.525	1.829	2.43	2.73	3.15
2016	2.223	3.137	2.026	2.807	1.898	2.31	2.45	2.99
2017	2.359	2.917	2.111	2.738	1.941	2.544	2.86	3.49
2018	2.552	3.216	2.24	2.929	2.075	2.742	1.85	2.60



(a) AR (b) MA (c) ARIMA

Fig. 5 Statistical features over many years using various models.



(a) Yearly and daily prediction (b) Trend and weekly prediction

Fig. 6 Breakdown of the forecast using prophet.

7 Results Interpretation

Mean Absolute Error for AR, MA, ARIMA and prophet are compared in Figure 8. As shown in the previous section, the best algorithm in term of fewer errors in most

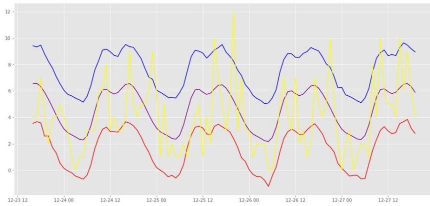


Fig. 7 Number of firefighters interventions using Prophet.

cases is ARIMA represented by the gray line. Among most of the years, starting from 2006 until 2018, this gray line has reached the minimum mean absolute error and root mean squared error, comparing to autoregression, moving average algorithms and prophet tool. Thus, the second, third, and fourth places are reserved respectively for Moving Average, Autoregressive, and Prophet. Generally, since ARIMA(p,d,q) stands for Auto Regressive Integrated Moving Average, it is logical to conclude that it combines AR (parameter p) and MA (parameter q) models. Other than that, ARIMA ensures the stationarity of the model (parameter d), unlike AR and MA. Therefore, by applying the components of these two models together, the probability of making errors will be reduced as shown in the experiments. It is important to mention that ARIMA is more complex than applied algorithms since it requires more time to identify the excessive number of parameters p,d and q. In contrast, when comparing eXtreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) algorithms applied and experimented in [**?**] together with ARIMA from 2006 to 2014, it seems that ARIMA has the lowest root mean squared error values. However, XGBoost has the minimal RMSE values for 2015,2016 and 2017. This result reflects that XGBoost is better for long term forecast usage.

On the other side, by analyzing the prophet result, it is very clear that the number of interventions of firefighters increments highly during the weekend (Saturday and Sunday) and reaches the minimum during the middle of the week (Wednesday). This interpretation corresponds to official days off in France. Also, the number of interventions increments slightly starting the month of May and reaches the maximum in July, then decreases gradually till November. The fluctuation of interventions per month reflects that during summer incidents are more likely to happen than other seasons. On the other hand, the daily seasonality illustrates that the number of interventions increases during the morning starting around 5:00 am and reaches higher values between 11:00 am and 5:00 pm. It's very logical to link this variation with the departure and return time from work.

8 Conclusion and Future Work

In this paper, Autoregression, Moving Average and Auto Regressive Integrated Moving Average has been implemented as well as a Facebook tool for time se-

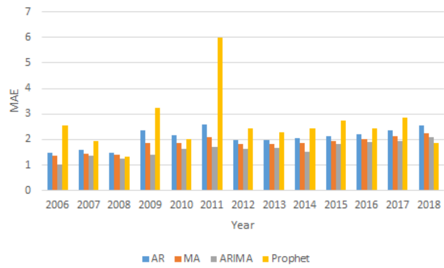


Fig. 8 Mean absotule error comparison for AR, MA and ARIMA.

ries forecasting called Prophet. For each model, statistical parameters have been calculated and compared between each other then compared between other results previously done. In general, as many researchers agreed, no hypothesis or rule electing a better algorithm among all-time series forecasting. The choice of the technique used depends on the specific prediction problem taking into account trends, seasonality, variables, size of the dataset, etc... In this paper, the statistical metrics indicate that ARIMA is the best model comparing to AR and MA as it combines first, the characteristics of these two algorithms and second the stationarity of the model. In contrast, XGBoost fits better than ARIMA for long term prediction. An extension to this work would be to apply different time series forecasting models to firefighters dataset.

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