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Predicting Passenger Flow at Charles De Gaulle Airport using Dense Neural Networks

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Security checking is a major issue in airport operations. Affecting the correct number of security agents is essential to provide a good quality of service to passengers while providing the best security performances. At Paris Charles de Gaulle airport the affectation of security agents is decided at strategical level, more than a month in advance. The key element to determine the number of agents needed is the passenger flow through the security checkpoints. This flow is correlated to the passenger flow in the different boarding rooms. This paper investigates the interest of small dense neural networks to perform passenger flow prediction at strategical level for Paris Charles de Gaulle airport. A dense neural network has been trained to predict the passenger flow for each boarding room of the airport. The network has been compared to a more complex long short-term memory model in terms of mean absolute error and outperformed a mathematical model based on exponentially modified Gaussian distribution.

Key Words : Airport Operations, Passenger Flow Prediction, Dense Neural Network, Strategic Prediction

1 Introduction

Passenger flow is the cornerstone of airport operations. The airport must constantly balance the quality of service it provides to its passengers with the associated costs. The waiting time perceived by passengers at security or border police stations relates to the quality of service of an airport. The maximal number of passengers handled at these key points depends on the number of positions open and the number of employees assigned to them. Therefore, managing human resources is essential to provide a quality of service while reducing operational costs.

At Paris Charles de Gaulle airport, security agents schedules are planned each month 45 days in advance. Small adjustments can be made 20 days upstream. Minor last minute changes are possible up to the week preceding and the day before. The later the change, the higher the cost. Therefore, the airport requires the most reliable prediction of its passenger flow 45 days in advance.

In a context of reducing the environmental impact of data science, reducing the size and structure complexity of neural networks becomes a major issue.[1)] The use of small dense networks instead of more complex structures can allow to obtain high quality results while reducing the necessary computational effort.

This paper investigates dense neural networks to predict passenger flow at Charles de Gaulle airport. The study presents the results for different boarding rooms of the terminal 2 of CDG airport (Figure 1):

- C2F - F1 and F2
- C2E - S3 and S4
- C2D - D53 and D62
- C2A - A40 and A47
- CT2 - A

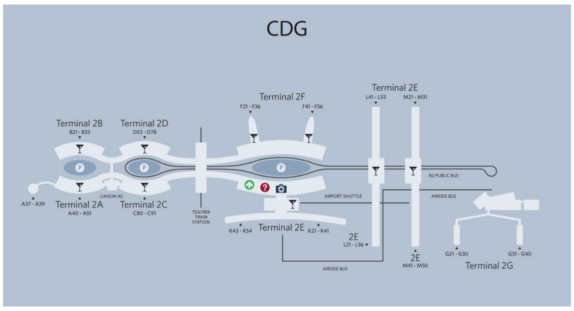

Fig. 1: Overview of Paris CDG Airport.

Section 2 presents a brief state of the art, Section 3 describes the structure of the neural networks and the extraction of features. Section 4 describes the results obtained with the method and compares it with other methods presented in the literature. Section 5 concludes the paper and suggests future improvements.

2 Prior work

In the literature predictions of passenger flows is mainly based on historical data. An exhaustive review has been done in 2017 by Liu and Chen[2] describing the different developed methods in the different transportation areas. In 2012 Wei and al.[3] predicted road traffic by decomposing the historical time series into different oscillatory modes. They then used a dense neural network to predict the most correlated modes to the original series and reconstruct it. Following the same principle in 2015, Sun and al.[4] used wavelets to decompose the time series into different oscillatory modes. Then, a Support Vector Machine (SVM) was trained to predict the modes and then finally the time series was reconstructed. Other decomposition of the passenger flow have also been studied. Hybrid seasonal decomposition method was proposed by Xie and al. in 2014.[5] In this method authors decompose the series into three components: daily, seasonal and irregular and predict them using support vector regression. Kumar and al. in 2015[6] enhanced the Autoregressive Integrated Moving Average (ARIMA) program by adding a seasonality component, creating the Seasonal ARIMA (SARIMA) program. Kumar also proposed a method of time series prediction based on Kalman filtering in 2017.[7]
Concerning the neural network approach, Liu and al.[2] developed an improvement of dense neural networks to predict the passenger flow. In their paper, an unsupervised stacked autoencoder (SAE) is created to set the initialization weights and biases of a dense neural network. In most of the scenarios studied, the network initialized by the SAE performed better than the dense network alone. A different approach based on mathematical modeling was explored by Buire and al. in 2021.[9] In their paper, they modeled the shape of the distribution of the passenger flow of each flight using an exponentially modified Gaussian distribution (EMG).[10] This distribution appears in many natural phenomenons[11] and its parameters can be fitted to describe the distribution of passengers arriving at security checkpoints before a flight. However, the accuracy of predictions made with this method may be limited, in particular when the passenger flow is close to zero. A different type of neural network was used by Monmousseau and al. in 2020.[8] In their model, authors use a recurrent neural network made of 200 LSTM cells to predict the passenger flow on some key points of the Paris Charles de Gaulle airport. Authors indicate that in the case of an airport, an overestimation does not have the same cost as an underestimation. In order to take this specificity into account, the loss function of the neural network was modified from a standard Mean Squared Error (MSE) to an $\alpha - PMSE$ which penalizes more severely the over-estimations of the passenger flow. With E_- and E_+ being respectively the underestimation error and the overestimation error, this loss function is given by the formula :

$$\alpha - PMSE = \frac{1}{|Data|} \sum_{Data} (E_- + (1+\alpha)E_+))^2 \quad (1)$$

Authors also mention the difficulty of describing and learning the operation of a security checkpoints within an airport using only historical data.

This difficulty was also mentioned by Wilson and al.,[12] when they proposed the Security Checkpoint Optimizer (SCO) in 2006. They introduced a program to simulate the passenger flow and thus, simulate the impact of a modification of the security checkpoint before applying it in reality. To model a security checkpoint, Leone and al.[13] proposed a modeling of each element of the checkpoint such as X-ray scanners, hand searches, explosive trace detectors etc. In that way, they quantified the performance of a checkpoint in order to propose improvements and limit the waiting time of passengers to ten minutes. To control the passenger flow, Lange and al.[14] introduced a virtual queuing system. This virtual queuing system give the passenger a time window to go to the security checkpoint. This methods allows to control at any time window the number of passengers in the checkpoint.

The difficulty of modeling the passenger flow in an airport limits the performance of prediction tools such as SVMs. However, more sophisticated networks such as LSTMs require significant computing power and learning time. The difficulty of prediction comes essentially from the large number of factors that influence the time series. Applying a "divide and conquer" strategy, by predicting each flight individually, would allow to obtain good quality results while limiting the required resources.

3 Model creation

This section presents the creation of the passenger flow prediction model and the features extraction from the data.

3.1. Principle of passenger flow prediction

As shown in Section 2, passenger flow prediction is to determine the time series of the number of passen-

ger passing through certain key areas. The literature presents predictions of the entire time series based on the data of the day such as in[8)]. This paper predicts the time series of a complete day by summing up the different passenger flows, predicted with a simpler neural network for each flight.
At the Paris Charles de Gaulle airport, the type of flight (short, medium or long haul) affects the room in which boarding will take place. Then, the type of flight influences the time distribution of passengers at the checkpoint. For example, airlines will ask passengers to present themselves earlier for long-haul flights. Therefore, the neural network breaks up into several neural networks tailored to each boarding room.

3.2. Data extraction

The dataset provided by Paris Charles de Gaulle airport covers nine months of passenger flow at each boarding rooms, from April 1^{st}, 2019 to December 31^{th}, 2019 with a time resolution of 10 minutes. This dataset avoids COVID-19 impacts on air traffic in 2020 and 2021. Therefore, the model will be more likely to perform well when traffic returns to normal.

For each passenger scanned at the security checkpoint and for each flight the scan data gives directly:

- Expected number of passengers on the flight
- Estimated time at the gate
- Type of movement (departure or arrival)
- Origin (if arriving flight) or Destination (if departing flight

From the date are extracted:

- Weekday
- First and last day of a weekend
- Holidays
- First and last day of holidays
- Public holidays

From the origin/destination a feature is extracted:

- Type of country

This feature represents whereas the flight is from France to France, France to a Schengen country or France to another country.

Weather data are not considered because a principal component analysis demonstrates its negligible impact. Figure 2 shows the explained variance as a function of the number of features used. The curve flatten on the last three features (which represent weather data). A flat curve indicate that the corresponding features do not add any useful information for the prediction.
This extraction results in a vector of 10 features for each flight which will be given as an input to the neural network.

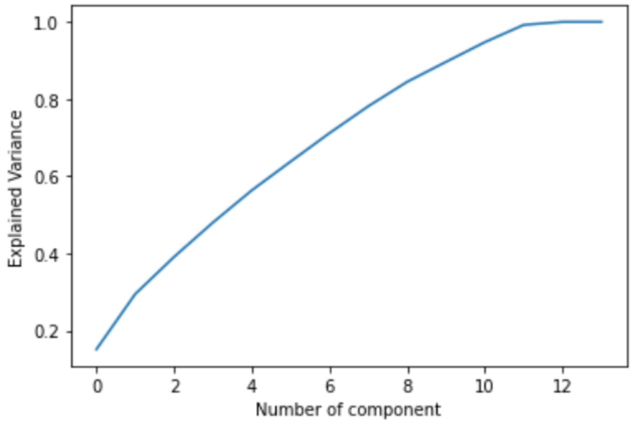

Fig. 2: Explained variance ratio obtained with a principal component analysis performed on the data. Features 11, 12 and 13 represents weather parameters (rain quantity, minimal temperature, maximal temperature).

3.3. Dense neural network creation

In order to predict the passenger flow at the different boarding rooms, a dense neural network is implemented for each room. This type of network is simple to set up and allows to approximate, after sufficient learning, the behavior of a system. This type of network is generally composed of an input layer, several hidden layers and an output layer (Figure 3).

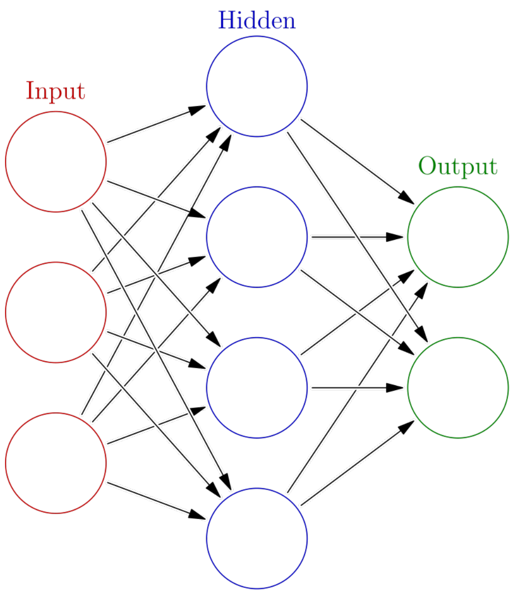

Fig. 3: Example of the structure of a dense neural network.

In our model, the input layer is the same size as a feature vector (10). The output layer contains as many neurons as the number of time steps in the time series (Figure 4). In that way, the network predicts for each flight the number of passengers entering the boarding room at each time step.

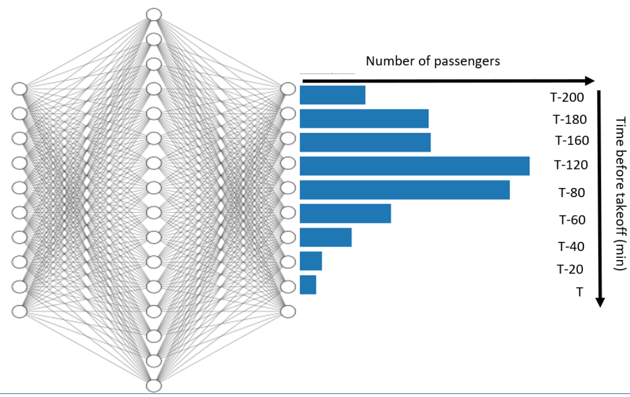

Fig. 4: Example of the extraction of the time series from the output layer.

After experiments carried out over the number and sizes of the different hidden layers, the structure retained for the study was chosen as follow: each network contains 4 hidden layers of size 16, 32, 32, 16 respectively . The activation function of each neuron is the Rectified Linear Unit (ReLu) :

$$\mathbf{ReLu}(x) = \max(0, x) \tag{2}$$

To avoid problems such as overfitting and vanishing gradient, dropout layers[16] were added between each of the hidden layers.
Table 1 summarizes the layers of the neural networks used in this paper.

Layer	**Shape**
Input	10
Dense 1	16
Dense 2	32
Dropout 20%	
Dense 3	32
Dropout 20%	
Dense 4	16
Output	

Table 1: Summary of a network structure used to predict the passenger flow.

The loss function chosen for the networks is the Mean Squared Error (MSE). Let D be the train set and h the learning model, the MSE of h over D is given by the equation :

$$\mathbf{MSE}(h, D) = \frac{1}{|D|} \sum_{(x,y) \in D} (h(x) - y)^2 \tag{3}$$

3.4. Model evaluation

To evaluate the predictions done by the networks, several metrics were chosen in order to compare the time series predicted to the actual passenger flow.

First, the Mean Absolute Error (MAE) gives the difference between the two time series. The smaller the MAE, the more accurate the prediction. This metric is given by the following formula :

$$\mathbf{MAE}(h, D) = \frac{1}{|D|} \sum_{(x,y) \in D} |h(x) - y| \tag{4}$$

The coefficient of determination R^2 evaluates the quality of the results. This score is given by the following equation :

$$R^2(h, D) = 1 - \frac{\sum_{(x,y) \in D} (y - h(x))^2}{\sum_{(x,y) \in D} (y - \bar{y})^2} \tag{5}$$

Where y is the value to be predicted, $\bar{y}$ the mean of y, $h(x)$ the prediction of the model with the input x and D the dataset.
The value of the R^2 score ranges from $-\infty$ to 1. If the score hits 1, it means the model h makes a perfect prediction. A R^2 of 0 means the model is as performing as constantly predicting the mean of the value each time. And a negative coefficient of determination means that the model is worse than just predicting the mean value each time and that the model does not give any useful prediction.

4 Results

For each boarding room, the dataset has been randomly split into two parts. 80% dedicated for training and the remaining 20% for validation. Each network described by the structure presented in the Section 3 has been trained during 30 epochs over the training set. Training was performed with a standard back-propagation algorithm using Adam optimizer[15] on a CPU Intel i5-1135G7 2.40 GHz. The performances of the model are computed using the metrics described in Section 3.4.. The performances are compared to the performances of the LSTM-200 model of Monmousseau and al.[8] and the exponentially modified Gaussian distribution of Buire and al.[9] . Unfortunately, the data provided by CDG airport do not match perfectly those used in the article by Monmousseau and al.[8] and Buire

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and al[9] . Thus, the comparison with their work could only be carried out on certain departure rooms for[8] and on the total number of passengers at the airport for[9] .

4.1. Passenger flow on individual flight

In order to predict the total passenger flow at each departure room, the chosen approach relies in predicting the passenger flow of each flight separately. Unlike what can be found in the literature where the prediction is directly performed on the total flow (except for[9]), here the flow is obtained by adding all the individual passenger flows of each flight.
For each of the studied boarding rooms, one neural network was implemented according to the structure represented in Table 1. An example of passenger flow prediction on an individual flight is displayed in Figure 5.

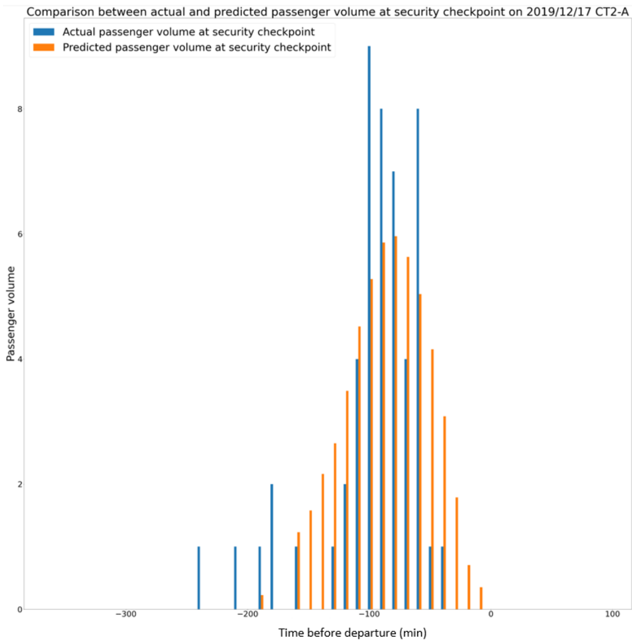


Fig. 5: Comparison between the actual passenger flow (blue) and the predicted passenger flow (orange) on an individual flight in the room CT2-A of CDG airport on 2019/12/17.

In order to validate the distribution given by the network, results are compared to the results obtained by Buire and al.[9] with the EMG distribution method (Figure 6).

The main problem that can be seen with EMG method is the convergence to zero of the first part of the curve. This part of the curve will never reach zero, so the model will always predict a non-zero number of passengers long before the scheduled departure of the flight.

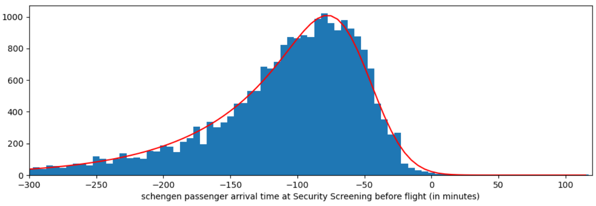


Fig. 6: Mean predicted passenger flow before departure on an individual flight using exponentially modified Gaussian distribution[9] .

Moreover, when all flights are summed up to determine the total flow of passengers, the addition of the falsely predicted passengers will give a non-negligible number of passengers predicted at times when there should not be any. This defect is particularly visible in Figure 9a between midnight and 4:00 am when there should be no passenger in the departure rooms.
With a neural network this problem does not arise, because as the learning process proceeds, the network will give the value zero on the first neurons of the output layer. We can see in Figure 7 that the neural network approach allows to limit the prediction of passengers on the periods when no passenger are present.

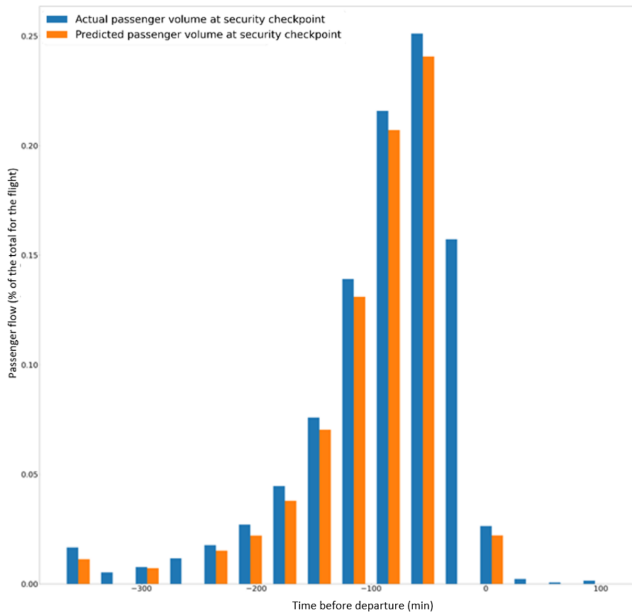


Fig. 7: Predicted mean passenger flow on an individual flight using Dense Neural Network.

Figure 7 shows that the network has well learned the distribution of the passenger flow in the boarding room for a flight. The MAE between the predicted and actual series in Figure 7 is about 0.049 which can be considered as highly satisfactory. Indeed, the shape of the predicted curve (in orange) closely follows the actual curve (in blue).

4.2. Total passenger flow prediction

At security checkpoints, passengers are not separated according to their flight. All passengers wishing to board in a certain room, will pass through the same checkpoint or the same set of checkpoints. What is important for the airport operator to know is how many checkpoints need to be opened and how many agents are required. This can be directly inferred thanks to passenger flow prediction. The idea presented here is to sum up all the passenger flows expected for each flight to obtain the global flow on each boarding room.

The evaluation of the total flow prediction for each boarding rooms is given in Table 2. The total flow of passengers at CDG airport is also showed in this table. A graphical representation of the predicted versus the actual passenger flow on one validation day for four different rooms is displayed in Figure 8.

	10 minutes time step		**1 hour time step**	
Room	**MAE**	**R^2 Score**	**MAE**	**R^2 Score**
C2F-F1	11	0.746	47	0.844
C2F-F2	13	0.751	51	0.869
C2E-S3	13	0.771	62	0.858
C2E-S4	4	0.896	16	0.971
C2D-D53	6	0.713	28	0.757
C2D-D62	2	0.605	12	0.679
C2A-A40	2	0.658	7	0.845
C2A-A47	2	0.541	5	0.812
CT1-B	1	0.654	4	0.810
TOTAL	**34**	**0.899**	**134**	**0.947**

Table 2: Performances of the model on the different boarding rooms of CDG airport.

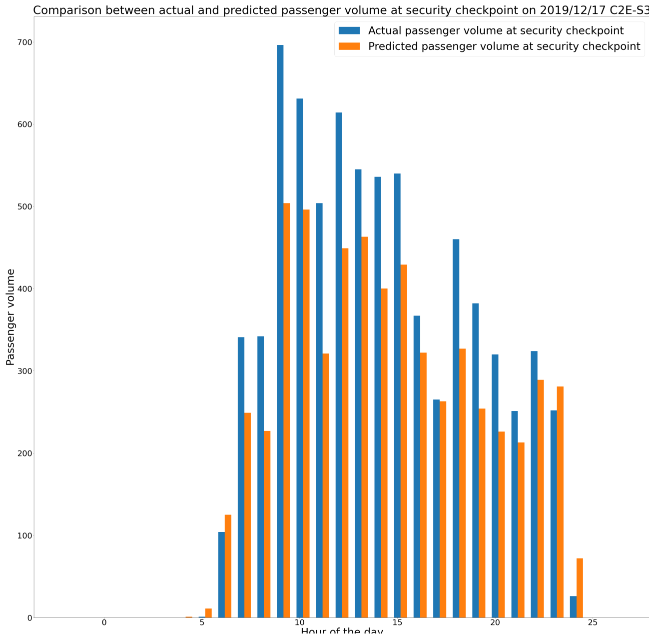
Table 2 shows a significant difference in terms of R^2 score as a function of time resolution. The use of a dense network does not allow the elements of the time series to be linked together as would have done a LSTM network. Thus, the smaller the time step, the more difficult it will be for the network to predict small variations in the time series. The smaller the time step, the lower the correlation between the predicted series and the actual series. This leads to a decrease of the R^2 score. However, in operations this decrease of the R^2 score would not be a significant problem. Indeed, the schedule of security agents does not require a 10 minutes precision and uses rather a time step of one hour. Table 2 also shows a significant difference in performance between the different rooms. This difference can be explained by the difference in the number of flights for each room. Each boarding room does not receive the same number of flights, and a room with more flights means a larger amount of data for the neural network. Rooms with less flights like C2A-A47 or C2D-D53 have less training data which implies that their networks are more likely to be less performing.

4.3. Comparison with prior work

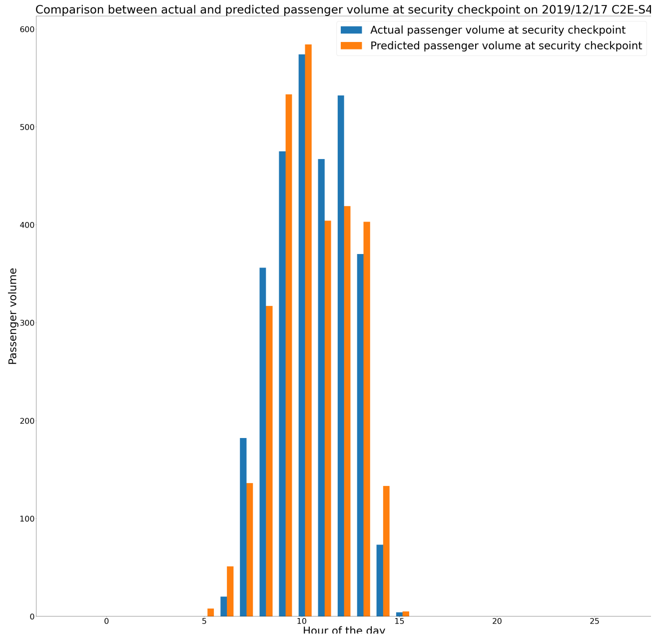
The paper of Monmousseau and al.[8] gives predictions over the passenger flow in the C2F terminal. This terminal is also available in our dataset. Therefore, the dense network can be compared with the LTSM200 of Monmousseau and al. The LSTM200 model gives a prediction with an MAE of 16 and an R^2 score of 0.86 with a 10 minutes time step in the best case on the C2F terminal. The dense network reaches the accuracy the LSTM200 in terms of MAE by reducing it to 12. But where an LSTM is specifically designed for time series predictions, the dense network struggle to have a strong correlation between the actual and predicted passenger flows. Therefore, the R^2 score of 0.75 obtained with the the dense network is lower than the 0.86 obtained with the LSTM.
Paper[9] present an approach which predict the total passenger flow over the entire airport using EMG. The two predictions of the total passenger flow on a same day are shown in Figure 9. The MAE given by authors on their result with the EMG is 305 which is more than two times bigger than the 134 obtained by the dense network. The R^2 score of the prediction obtained with the EMG is not given by the authors. Nevertheless, the R^2 score of 0.94 obtained by the dense network on the total can be considered satisfactory. In Figure 9a, a significant number of passengers was predicted between midnight and 4am with the EMG method. This issue did not append with the dense neural network as shown in Figure 9b.

5 Conclusion and perspectives

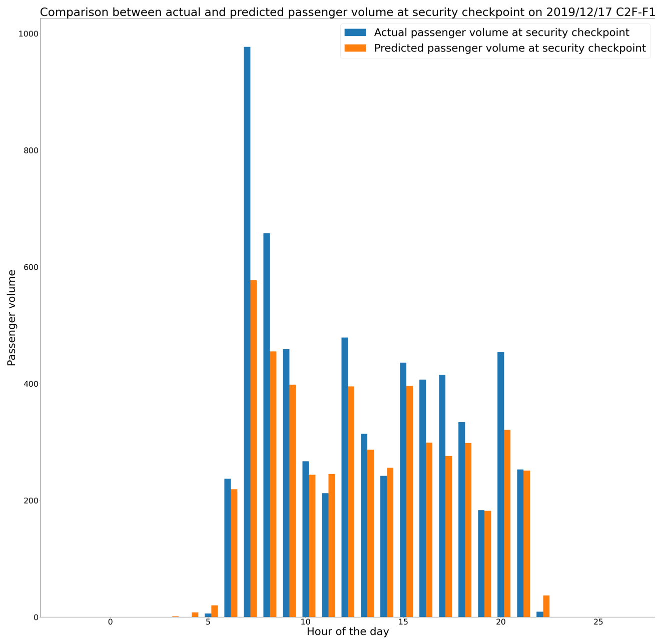
This paper investigates predicting the passenger flow at the different boarding rooms of Paris Charles de Gaulle airport with dense neural networks. Performances of such neural networks were evaluated using the MAE ans R^2 score. The results are promising since the model outperformed the exponentially modified Gaussian distribution model proposed in 2021 and gave equivalent prediction in terms of MAE as a more sophisticated LSTM model. This work shows that small dense networks can give, on specific problems, similar results than models requiring significantly more computational power. Thanks to the small computational



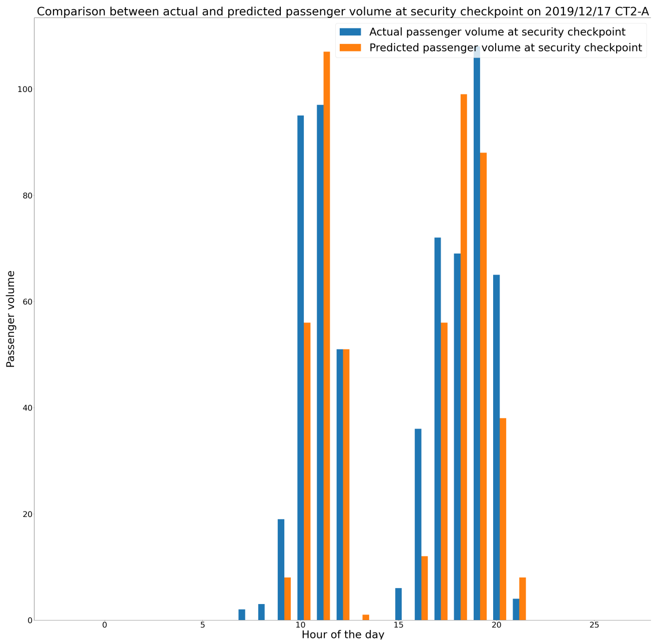
(a) C2E-S3



(b) C2E-S4

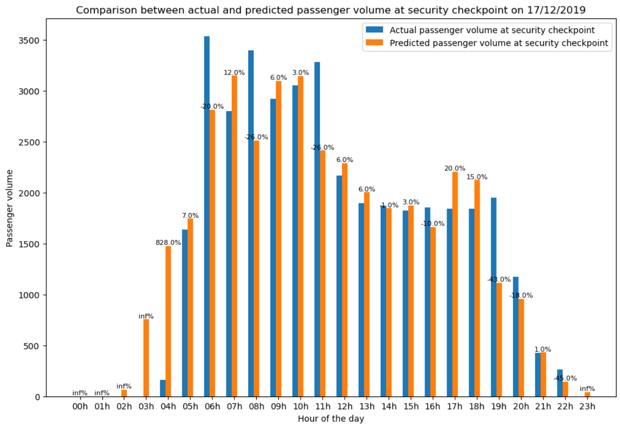


(c) C2F-F1

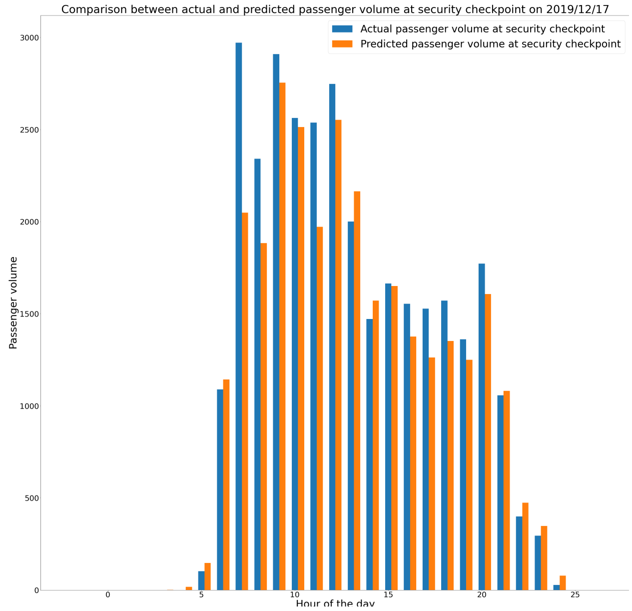


(d) CT2-A

Fig. 8: Comparison between predicted passenger flow (orange) and actual passenger flow (blue) at four boarding rooms (C2E-S3, C2E-S4, C2F-F1, CT2-A) of the CDG airport on 2019/12/17 with a time step of one hour.



(a) Total passenger flow with EMG method[9]



(b) Total passenger flow with dense neural network

Fig. 9: Comparison between predicted and actual total passenger flow at CDG airport on 2019/12/17 with a time step of one hour.

power needed, this method could be tested in operation in order to validate the performances obtained in this study. Future work should investigate fine tuning the parameters of the network such as modifying the activation functions of the hidden layers. Structure optimization such as network pruning can also be performed to enhance networks performances.

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