Brazilian Journal of Technology

Predictive Demand Service for Public Transit Using CNN

Atendimento Preditivo de Demanda do Transporte Público Coletivo Usando CNN

DOI:10.38152/bjtv3n4-003

Recebimento dos originais:03/10/2020
Aceitação para publicação:16/11/2020

Willgnner Ferreira Santos
Curso de Engenharia da Computação, PUC Goiás
ECEC, PUC Goiás
Av, Universitária 1.440, Setor Universitário, Goiânia-GO, CEP: 74605-010
E-mail: willgnnersantos@gmail.com

Leonardo Guerra de Rezende Guedes
Doutor em Engenharia Elétrica e de Computação pela UNICAMP
MDPT, PUC Goiás & EMC, UFG
Av, Universitária 1.440, Setor Universitário, Goiânia-GO, CEP: 74605-010
E-mail: prof.leonardo.guedes@gmail.com

Olegário Corrêa da Silva Neto
Mestre em Engenharia Elétrica e de Computação pela UFG
ECEC, PUC Goiás
Av, Universitária 1.440, Setor Universitário, Goiânia-GO, CEP: 74605-010
E-mail: olegarioneto@gmail.com

Eugênio Julio Messala Cândido Carvalho
Mestre em Engenharia Elétrica e de Computação pela UFG
ECEC, PUC Goiás
Av, Universitária 1.440, Setor Universitário Goiânia-GO, CEP: 74605-010
E-mail: eugeniojuliomessala@gmail.com

Douglas Vieira do Nascimento
Curso de Engenharia da Computação, PUC Goiás
ECEC, PUC Goiás
Av, Universitária 1.440, Setor Universitário, Goiânia-GO, CEP: 74605-010
E-mail: douglaz.vieira.n@gmail.com

ABSTRACT
Several cities in Brazil undergo a territorial expansion and inhabitants constantly, this process is called urbanization. An uncontrolled urbanization generates many difficulties, highlighting the mobility of public transport, since many citizens depend on this mobility, we have, for example, public transport in Goiânia, which directly affects the living conditions of passengers. For your foreknowledge, a model capable of mirroring the performance of your demand is essential, providing that the system meets users in an acceptable way. A two-dimensional CNN is a CNN model that has a hidden convolutional layer that operates on a 1D sequence, it is a convenient mechanism to simulate a univariate forecast of time series of the predictive service of Goiânia's public transport. The method is equivalent to an analysis of the focal parts that make up the public transport system and how to represent it in the 1D convolutional

neural network. Actual data of the systems and their results were compared to those expected, showing the model's effectiveness. This work manifests a forecast of the demand for public transport in Goiânia, to make it susceptible to users of the system.

Keywords: Public transport, CNN and Computer Simulation.

RESUMO
Várias cidades do Brasil sofrem uma expansão territorial e de habitantes constantemente, esse processo é chamado urbanização. Uma urbanização descontrolada gera muitas dificuldades, ressaltando a mobilidade do transporte público, visto que um vultoso número de cidadãos depende dessa mobilidade, temos por exemplo o transporte público de Goiânia, que abala diretamente a condição de vida dos passageiros. Para sua presciência é essencial um modelo capaz de espelhar o desempenho de sua demanda, proporcionado que o sistema atenda os usuários de forma aceitável. Uma CNN bidimensional é um modelo da CNN que possui uma camada oculta convolucional que opera sobre uma sequência 1D, é um mecanismo conveniente para simular uma previsão univariada de séries temporais do atendimento preditivo do transporte público de Goiânia. O método equivale em uma análise das partes focais que constituem o sistema de transporte público e como representá-lo na rede neural convolucional 1D. Dados reais dos sistemas e os seus resultados foram contrapostos os esperados, apresentando a eficácia do modelo. Esse trabalho manifesta uma previsão da demanda do transporte público de Goiânia, para torná-lo suscetível aos usuários do sistema.

Palavras Chaves: Transporte público, CNN e Simulação Computacional.

1 INTRODUCTION

Public transport in Brazil has always been the subject of many complaints over time. Most of the time, the complaints refer to the fact that the vehicles are always full, the bad conditions of the cars and the low quality of the services provided. The population's dissatisfaction with public transport in Brazilian cities, however, is not a recent issue. Research conducted by the Institute for Applied Economic Research (IPEA), in 2011 and 2012, revealed a negative picture, with assessments classified as “terrible or bad” exceeding 60%

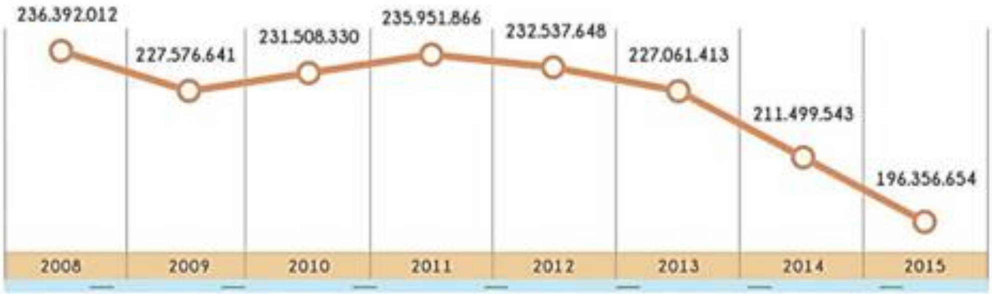
Urban mobility is a fundamental theme when discussing urban development and the quality of life of the population. The conditions for displacement of people and goods in urban centers impact the entire society by generating negative externalities, such as accidents, pollution and congestion. (CHR, CARVALHO, 2016).

Among the main solutions to the problem of urban mobility, in the view of many experts, it would be the encouragement of public transport, through the improvement of its qualities and efficiencies and the development of traffic focused on the circulation of these vehicles. In addition, encouraging the use of bicycles, especially with the construction of bike lanes and bike lanes, can also be an option to be better worked on. (PENA, RODOLFO F. ALVES, 2020).

In creating the system, artificial neural networks will be used, which consist of evolutionary systems that based on past data, can end acceptable solutions to the problem. These past data are demand statistics (Figure 1) released by SET, which show the demands of users from 2008 to 2015 (Source:

SET, 2017).

Figure 1: RMTC's Annual Demand since 2008.
(Source: SET, 2017).



In view of the panoramas, this work suggests a model to make the public transport system look like and to assist in the deliberations the reverence of the line's performance, looking for efficiency and low costs of the system.

2 THEORETICAL FOUNDATION

In recent years, computer simulation has assumed an increasing importance as a knowledge acquisition tool. In the simulation developed at the beginning of the Operational Research, the problems were solved by obtaining the best possible results for each individual part of the model. However, as the complexity of the problems grew, the need arose to use a more systemic and generalist approach. (GAVIRA, M. O. 2003).

Convolutional Neural Networks (CNN) are quite prevalent in the field of computer vision due to their advantages: translation invariance, parameter sharing and sparse connectivity. Its use, unlike traditional approaches that use pre-processing of the signals in a statistical way for later use in learning an ANN, allows the data to be used in its raw form, eliminating the need for any computational processing other than that dispensed with learning itself. The idea behind deep learning is to discover multiple levels of representation with the expectation that high-level resources will represent a more abstract semantics of the data. (GUO et al., 2017).

> ” Deep learning techniques in ANN have been applied to many fields where they produce results, in some cases, superior to those obtained with human specialists.” Deep Neural Networks - Deep Neural Network (DNN), Recurrent Neural Networks - Recurrent Neural Network (RNN), and Convolutional Neural Networks - Convolutional Neural Network (CNN) are the most frequently used deep learning architectures. (GUO et al., 2018, p. 3).

2.1 MODELING ITEMS OF PUBLIC TRANSPORT

Public transport can be broken down into many items that expose the manner of the degree of the system, below are the most important items:

- Terminals: entrance of the bus line and the end of it, all lines must have terminals;
- Stops: line stops, either on boarding or disembarking;

Brazilian Journal of Technology

- Direction: represents the direction that the lines will follow, either clockwise or in reverse, the lines can follow only one direction as well;
- Route: define the route that the lines will take, whether on the streets, avenues, highways, the time of the route is also defined;
- Vehicle: class of transport that will serve the lines, be it buses, airplanes, ships etc.

On some occasions, the lines may suffer a drop in passengers, causing losses, one of the solutions would be to create alternative lines to meet this demand and to be able to complete the route of other lines that are dropping passengers, defining the route times to make the route more flexible. attendance and attend all.

2.2 TIME SERIES

According to the statistical definition, a time series is a collection of sequential data obtained over time (Ehlers, 1999). The order of observations may be irrelevant for linear regression, but it is essential for the analysis of time series. Its objective is to identify some dependence between the neighboring T observations of a series $Z_T = (Z_1, Z_2, ..., Z_T)$ and to build a mathematical model from which it is possible to predict future values for the series.

It is necessary to define not only the forecast horizon, but also the window to be used. The first relates to the number of subsequent values that will be expected; the second regularizes the number of elements prior to what will be expected (Ehlers, 1999). The forecast horizon can be classified as short, medium and long term. The longer the forecast horizon, the greater the chance of errors, so short-term forecasts provide a good view of the near future with a low error.

Some series are called stationary, that is, over time, the series remains around a constant average. Others have trends, and may have a positive or negative inclination, called a linear trend. Among some methods of forecasting time series can be mentioned the Simple Moving Average, the Weighted Moving Average, the Exponential Moving Average, and the Forecasting of Time Series subject to seasonal phenomena (Nogueira, 2005). The methods used in the comparative study of this project are detailed below.

2.3 CONVOLUCIONAL NEURAL NETWORK

The application of convolution layers in data sets can be used as an extractor of characteristics implicit in the data. Convolution in two signals related to time and function f and g respectively, is defined by

$$(f * g)(t) - h(t) - \int_{-\infty}^{\infty} f(r) * g(t - r)dr$$

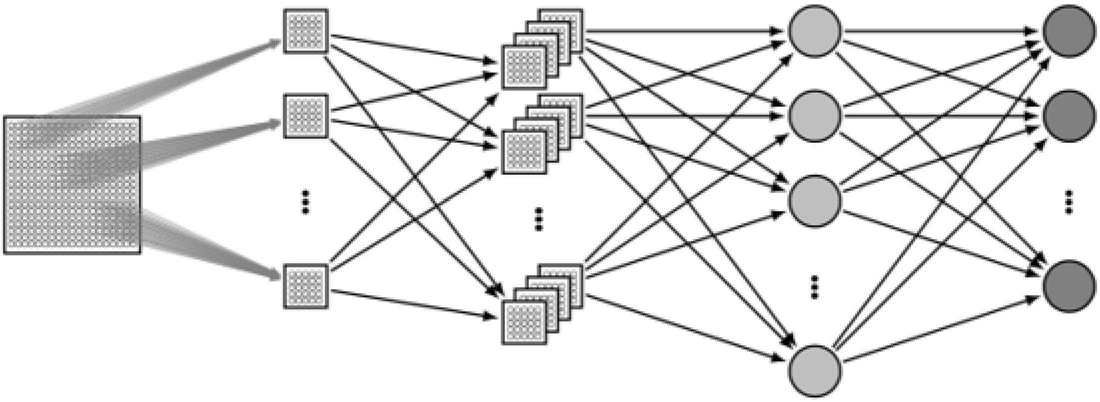
Brazilian Journal of Technology

A CNN is an architecture composed of at least four distinct layers: an input layer, a convolutional layer with its respective activation function, a dense layer pooling layer responsible for making the regression or classification. The k parameter specifies the number of resource maps in the convolutional layer.

$$(f * g)[n] \equiv \sum_{m=-\infty}^{\infty} f[n-m]g[m]$$

Where f is the input layer and g are one of the k filters that CNN will optimize for an objective function during the learning process. (LOCA, ANTONIO; RAUBER, THOMAS, 2019).

Figure 2: Topology of the Convolutional Neural Network.



(Source: SAKURAI, RAFAEL, 2017).

The CNNs differential is in the various convolutional layers, which apply a mathematical function of Convolution of the input data and then performing the Pooling. The output of the convolution is passed to the next convolutional layer until it reaches the last layer known as the Dense Layer, which is usually represented by a multilayer Perceptron network (Multilayer Perceptron - MLP). (SAKURAI, RAFAEL, 2017).

For this work a one-dimensional CNN was used, it is a CNN model that has a convolutional hidden layer that operates on a 1D sequence. This is followed by perhaps a second convolutional layer in some cases, such as very long input strings, and then a pool layer whose job is to distill the output from the convolutional layer to the most salient elements. (GONZALEZ, RAFAEL, 2010).

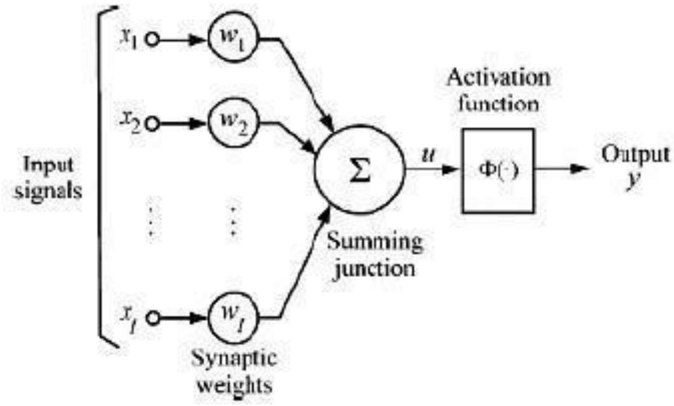
The convolutional and pool layers are followed by a dense and fully connected layer that interprets the resources extracted by the convolutional part of the model. A flattened layer is used between the convolutional layers and the dense layer to reduce the resource maps to a single one-dimensional vector. (GONZALEZ, RAFAEL, 2010).

Brazilian Journal of Technology

3 METHODOLOGY

The project consists of a process of developing a system capable of predicting future demands on urban public transport and proposing the number of buses needed to meet this demand, where to predict future demands and the number of buses needed, artificial neural networks will be used , to better address the problem, the convolutional neural network 1D was chosen.

Figure 3: artificial neuron.



(Source: LUDVIG, 2017).

An artificial neuron to be activated, must have its inputs multiplied by w values, which are called synaptic weights, after being added to a single value and passed to a function, called an activation function, which will give a result that will say whether the neuron was activated or not. Synaptic weights are those that dictate the influence of an input on the final output of an artificial neuron.

A set of neurons is called a layer and the junction of these layers is called multilayer neural networks, however, for there to be a neural network it is necessary to have at least one input layer and one output layer and it is very common that in the input layer there are no neurons and only elements that propagate the inputs to the next layer (PANDO et al ,. 2018).

For the ANN to be able to recognize patterns it is necessary that its synaptic weights be adjusted based on the comparison between the set of predefined outputs with the outputs obtained by the execution of the neural network, this process is called learning and it makes the neural network capable of predict results for inputs that do not have predefined outputs.

An ANN has some parameters that define its behavior, such as the learning rate, which dictates how much the synaptic weights must be adjusted for each training interaction, the synaptic weights, which indicate how much an input influences that neuron and the bias, which they help to increase the speed of convergence of the network, however it is not a mandatory element.

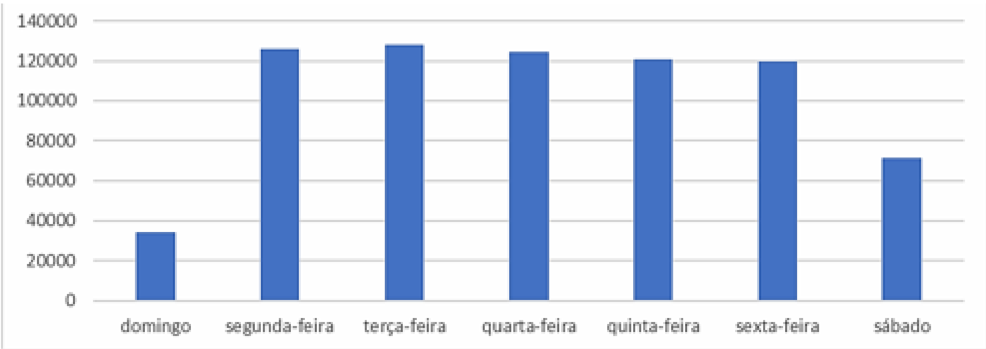
In ANN training, in addition to the parameters, it is necessary to determine some stopping criteria that are responsible for preventing the network from losing its ability to generalize, that is, the ability to predict unknown values. Usually to prevent this, a maximum acceptable error and / or a maximum number of training iterations that the network can have is defined (GUEDES, 2018).

Brazilian Journal of Technology

In order to design an ANN, one must determine the number of inputs, number of hidden layers and the number of outputs, in addition to synaptic weights and training stop parameters, to determine optimal values for all these variables there are some discussions about mathematical methods to obtain them, however the most common is trial and error, that is, several RNAs are tested and discarded until an RNA is found that presents a satisfactory result.

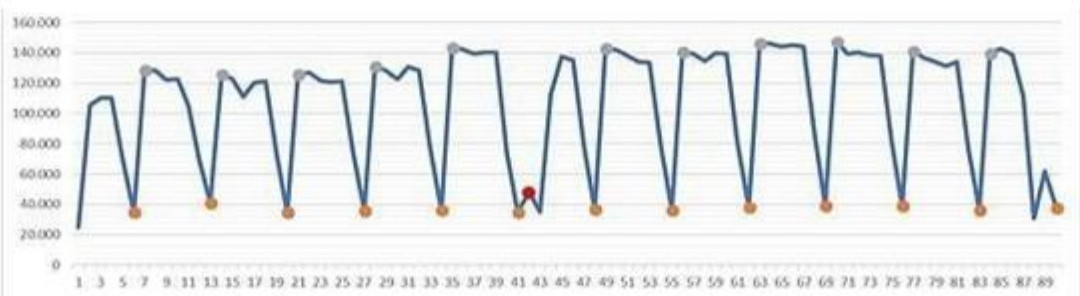
The methods that will be used to solve the problem, followed by the search for statistics and data that can help in the solution and so that these data can be used as input to the neural networks are in Figures 4 and 5.

Figure 4: Distribution of demand for the Anhanguera axis by weekdays from 2013 to 2016.



(Source: CMTC, 2018).

Figure 5: Demands from 2013 from January to March and their behavior on Sundays and Mondays.



(Orange dots represents Sundays. Source: the authors, 2018).

The design of a simulation consists of the process of building a model divided into steps (Law and Kelton, 2001), some steps in the process of creating the simulation deserve to be highlighted.

The first step is to formulate the problem that gives rise to the objectives, this step must be done very carefully so that the scope of the simulation is defined and avoid creating a model that does not meet expectations or a model in which construction is impossible. (Law and Kelton, 2001).

Soon after, the data must be collected, this is a continuous process, because as the model progresses the data will be incorporated into the simulation and new collections become necessary. The collected data must seek to represent the main behaviors of the model and meet the scope that was defined in the previous step. (Law and Kelton, 2001).

Finally, it should be noted that the model must be closely monitored and its operation monitored, so that possible problems are identified and corrected, increasing the chance of validating it with the real environment and the experimentation can be done correctly to demonstrate the various scenarios of interest. (Law and Kelton, 2001).

3.1 EXPLANATION OF THE PROBLEM AND PURPOSES

The explanation is to intend a computer simulation that causes the circumstances of public transport and try to make the system sensible to the demands of users, trying to predict the presumed errors and generate alternatives to correct them or seek an appropriate solution when there are problems, the computer simulation will predict the demand for public transport for the last 30 days of each month.

After all the problem definitions were defined, the initial progress was to accept the components of the system and later represent them in the 1D convolutional neural network. We have as components the number of passengers who boarded the 001-Eixo Anhanguera line, from 2013-2016, from Monday to Sunday, these components were essential for the execution of the system.

In the system adjustment phase, some parameters of the model are chosen to produce its repair based on the difference between the real and predicted values by the model. The selected parameters are usually those that have a greater inaccuracy, that is, parameters with a more difficult purpose. The values of the parameters are calibrated by a statistical method, in order to improve a statistical indicator, most of the time the Root Mean Square Error or RMSE.

In addition to the RMSE used in the model, the mean absolute error or MAE will be used, it represents the mean of absolute errors between predicted and observed values. The proposed expected model is defined by two different specifications: the root mean square error (RMSE) and the mean absolute error (MAE), both visualized in the equations below. These specifications are the data prediction metrics commonly used for data prediction model metrics.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|$$

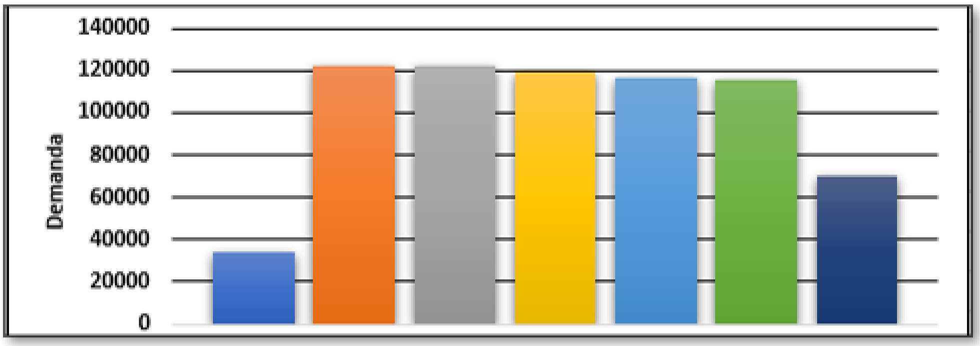
4 RESULTS AND DISCUSSION

The demand for public transport has several particularities that are considerable to be addressed, the data detailed below, aims to point out those aspects that are intrinsic to public transport systems.

The data obtained, mentioned above, are from the 001-Eixo Anhanguera line, of the public transport system of the metropolis of Goiânia, which is the capital of the state of Goiás and were obtained from the Metropolitan Transport Company (CMTC).

Brazilian Journal of Technology

Figure 6: Daily Average Demand for Line 001 - Anhanguera Axis per weekday (Monday to Saturday).



(Source: The author).

As shown in the graph above, figure 6, the daily average demand for line 001-Eixo Anhanguera is displayed, the peak hour in the morning, takes place from 6:30 am to 7:30 am with 14,172 passengers on board, a difference in demand is noted during the days of the week, on Sunday this demand is quite reduced, together on Saturday, since these days of the week are not useful, on the other days the demand behaves level. (Source: CMTC, 2012).

Figure 7: Passenger shipments by time and direction on weekdays.

(Fonte: CMTC, 2012).

The current demand for the Anhanguera axis on working days is 230,770 passengers. This demand includes passengers boarding the aisle platforms and those who are part of the terminals. The two peak periods, morning and afternoon, represent 37% of daily departures, with approximately 87 thousand passengers, as can be seen in the Graph above, figure 7. (CMTC, 2012)

.

4.1 CNN 1D NUCLEUS

Appendix: Algorithms implemented.

Required Libraries.

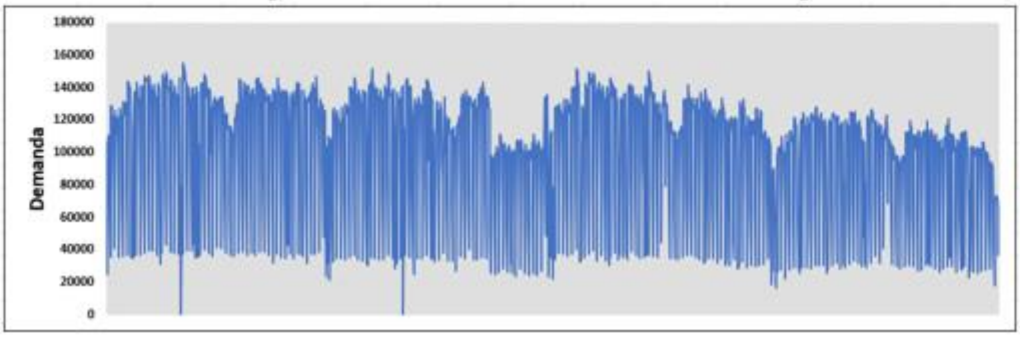
Brazilian Journal of Technology

```
from random import randint
import random
import math
import numpy as np # linear álgebra.
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv).
import seaborn as sns
import matplotlib.pyplot as plt
from keras.models import Sequential
from keras.layers import Dense,RepeatVector
from keras.layers import Flatten
from keras.layers import TimeDistributed
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
import os
print(os.listdir("../input/dadosbrutos")) # raw data is the dataset.
data=pd.read_csv('../input/dadosbrutos//demanda.csv') # the demand file contains 2013-2016 passenger shipments.
data.info()
# As we can see, the date is object and we have to convert date column to datetime. So we are going to use to_datetime function for the convert.
data.head() # Brief preview of the demand file.
data.info()
# We are going to convert hourly data to daily data.
df=pd.DataFrame(data)
plt.figure(figsize=(16,8))
data.plot()
plt.xlabel('Dias da semana, seg-dom, 2013-2016')
plt.ylabel('Demanda')
plt.show()
df_1=df.values
df_1=df_1.astype('float32')
scaler = MinMaxScaler(feature_range=(0,1))
ts = scaler.fit_transform(df_1
df.info()
timestep = 30
X=[]
Y=[]
raw_data=ts
for i in range(len(raw_data)- (timestep)):
X.append(raw_data[i:i+timestep])
Y.append(raw_data[i+timestep])
X=np.asanyarray(X)
Y=np.asanyarray(Y)
k = 1400
Xtrain = X[:k,:,:]
Ytrain = Y[:k]
```

Brazilian Journal of Technology

```
model = Sequential()
model.add(Conv1D(filters=128, kernel_size=2, activation='relu',
input_shape=(30, 1)))
model.add(Conv1D(filters=128, kernel_size=2, activation='relu'))
model.add(Conv1D(filters=128, kernel_size=2, activation='relu'))
model.add(MaxPooling1D(pool_size=2))
model.add(Flatten())
model.add(Dense(100, activation='relu'))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# fit mode.
model.fit(Xtrain, Ytrain, epochs=200, verbose=0)
Xtest = X[k:,:,:]
Ytest= Y[k:]
preds = model.predict(Xtest)
preds = scaler.inverse_transform(preds)
Ytest=np.asanyarray(Ytest)
Ytest=Ytest.reshape(-1,1)
Ytest = scaler.inverse_transform(Ytest)
Ytrain=np.asanyarray(Ytrain)
Ytrain=Ytrain.reshape(-1,1)
Ytrain = scaler.inverse_transform(Ytrain)
from matplotlib import pyplot
pyplot.figure(figsize=(20,10))
pyplot.plot(Ytest)
pyplot.plot(preds, 'r')
pyplot.show()
```

Figure 8: Simulated Time Series of Line 001-Axis Anhanguera

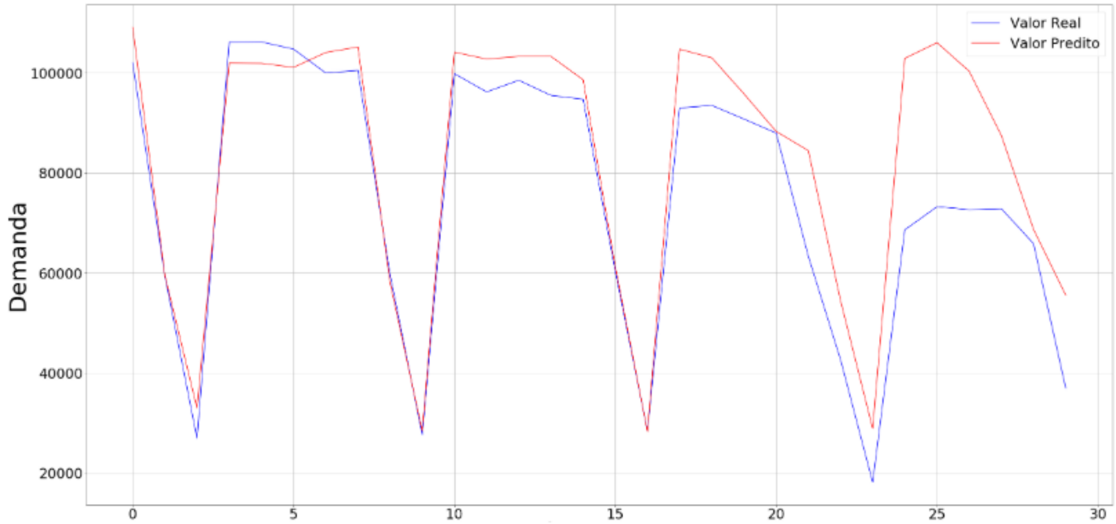


(Source: The author).

The graph generated above, figure 8, shows the result of the simulated time series of the 001-Eixo Anhanguera line, the demand is generated according to the number of passengers that board the line. The time series shows in the system its fickle during the days of the week, a change in the calculation of the average of the days of the week is noted, we can mention, for example, Monday's demand, which has a high peak, already on Sunday, the demand the line drops a lot.

The reason for the demand for the line falls a lot, it depends on several occasions, on Monday, because it is an academic day, it is normal for demand to be quite high, already on Sunday, which is not a working day and does not usually have students, workers, street vendors, among others, this demand for the line is very low.

Figure 9: Demand forecast for line 001-Eixo Anhanguera is days.



(Source: The author).

In order to predict the demand for transport, observing figure 9, the demands simulated by the model are very visually close to the predicted, they remain very close during almost the entire simulation performed, when calculating the RMSE and MAE were 0.0823 and 0.0573 respectively, such metrics should be as close as possible to 0 for good solutions.

5 CONCLUSIONS

With the evidenced data, it is understood that the simulation manages to follow the rhythm well of the real system, according to RMSE and MAE which were 0.0823 and 0.0573 respectively, the 1D convolutional neural network was able to accurately represent and predict the data and showed a micro view of the system, where the visualization of the system action is noticed, together with an overview. Some changes are essential to calibrate the system, for example, the inclusion of other vehicles to forecast the trains needed to serve users comfortably.

It is also worth mentioning that it is necessary to seek more data for CNN, since the data used in the system does not yet demonstrate 100% of the system's behavior, but the data used in the simulation were necessary to demonstrate the system, however much data obtained, it would be possible a more accurate classification of the problem presented.

With the results achieved and the difficulties noted at work, it is expected that this work can help studies and research on public transport simulations and can contribute to the labor market, together to help current systems and find a better use of the benefit provided , causing positive points for the population.

REFERENCES

SILVA, Julia Borges Correia et al. Algorithms applied to the multimodal transport problem. 2018.

Brazilian Journal of Technology

PANDO, Luciano Urgal et at. Evaluation of estimation techniques of the origin-destination matrix of vehicle traffic in cities. 2018. Master Thesis. Universidade Tecnológica Federal do Paraná.

GABRIEL DA SILVA SOUSA, C. et al. Predictability of Poissonian Urban Public Traffic. Brazilian Journal of Development, Curitiba, p. 20, 2019. ISSN ISSN 2525-8761.

KHAZAII, Javad. Genetic Algorithm Optimization. In: Advanced Decision Making for HVAC Engineers. Springer International Publishing, 2016.

CARVALHO, C. H. R. D. Urban Mobility: Advances, Challenges and Perspectives. Brasília – DF: Livraria Ipea, 2016.

GUEDES, Ítalo César Montalvão et al. Probabilistic model for investigating the influence of bus stops on urban vehicle traffic noise. 2018.

CASTRO, G.M. The impact of public infrastructure components on the growth of Brazilian cities: a spatial analysis from the period from 1970 to 2010. 2016. Doctoral Thesis. Universidade de São Paulo.

BRAGA, M. L., SANTOS, A. J., PEDROZA, C. P., COSTA, L. H. K. M., Route Planning with Anytime Algorithms in Vehicle Networks on the Raspberry Pi Platform, IV Simpósio Brasileiro de Engenharia de Sistemas Computacionais, 2014.

GAVIRA, Muriel de Oliveira. Computer Simulation as a Knowledge Acquisition Tool. 2003. 163 f. Master Thesis - Production Engineering Course, Universidade de São Paulo, São Carlos, 2003. Disponível em: <https://teses.usp.br/teses/disponiveis/18/18140/tde-20052003-004345/publico/Gavira1.pdf>. Access in 03 mar. 2020.

SET, Union of Urban Passenger Transport Companies in Goiânia, disponível em http://www.sitpass.com.br/site/institucionaI/seV, Access in 01/03/2017.

M. D. Zeiler and R. Fergus, Computer Vision – ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part I. Springer International Publishing, 2014, ch. Visualizingand Understanding Convolutional Networks, pp. 818–833.