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Pedestrian flow prediction in commercial avenue

Marwane Benhadou[1], Amina El Gonnouni[2], Abdelouahid Lyhyaoui[2]
[1]Laboratory of Economic Studies, Digital Analysis, and Artificial Intelligence, Faculty of Law Economic and Social Sciences of Tetouan, Abdelmalek Essaâdi University, Tetouan, Morocco
[2]Laboratory of Innovative Technologies, National School of Applied Sciences, Abdelmalek Essaâdi University, Tangier, Morocco

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ABSTRACT

Mobility plans are one of the most important management tools for city development and an important factor for society and economic growth, where pedestrians are the end goal of any mobility plan. Human behavior is generally unpredictable, and many attempts have been interested at pedestrians' mobility in urban environments, both microscopic and macroscopic (flow, density, and speed) levels. The objective of pedestrian traffic flow prediction is to predict the number of pedestrians at the next moment. Assisting operators and city managers in making decisions in urban environments such as emergency support systems, and quality-of-service evaluation. This study aims to model and predict bi-directional pedestrian flow in a commercial avenue, based on two essential stages, data collection through video recording over two months (pedestrian flow) and data analysis using machine learning algorithms that provide a lower error and a higher accuracy rate. Two metrics were selected as basic measures to evaluate the model performances, root mean square error (RMSE) and coefficient of determination R^2. Artificial neural network (ANN) gives a little better performance and fitness.

Corresponding Author:

Marwane Benhadou
Laboratory of Economic Studies, Digital Analysis, and Artificial Intelligence, Faculty of Law Economic and Social Sciences of Tetouan, Abdelmalek Essaâdi University
Martil Tétouan highway, Tétouan, Morocco
Email: marwane.feg.info@gmail.com

1. INTRODUCTION

Walking is an essential activity within urban centers, where various travel-attracting activities are concentrated (schools, hospitals, shopping centers, and administrative entities). This concentration of activity attractors causes congestion at the level of pedestrian flow, in addition, these areas are not always suitable to support high pedestrian flow, such as narrow or poorly maintained sidewalks with a variety of obstacles interposed, which offer a poor level of service to pedestrians. Therefore, the study of pedestrian flow aims to increase pedestrian safety, maintain the pedestrian network's continuity, encourage walking, and improve the quality of pedestrian service [1].

We chose as a study area a commercial avenue, where most of the stores and shopping centers are concentrated. This concentration causes a high demand in terms of pedestrian flow. Urban infrastructures must be adapted to support the level of service required (avoid congestion). The mathematical modeling of pedestrian movement is relatively complex, that's why we resort to experimental data such as pedestrian flow, defined as the number of pedestrians passing through an area in a specific time interval. Through the use of machine learning algorithms, we will model and predict pedestrian flow and thus have a tool to assist operators and city managers in making decisions in urban environments and controlling pedestrian crowds.

To understand pedestrian behavior in urban journeys, researchers use pedestrian movement modeling. They are differentiated into two categories: microscopic and macroscopic models. Microscopic models, evaluate the behavior of an individual pedestrian. In many studies conducted, such as cellular automata models CA, the method is based on the discretization of space in cells, each pedestrian occupies a cell with a direction of preference [2]. The social force model SF is based on the analogy with Newtonian physics, where the pedestrian is subjected to attraction forces and repression which act on its acceleration [3]. In other studies, based on discrete choice models, where researchers model walking alternatives based on factors, such: as speed, radial direction, and the number of pedestrians present [4].

On the other hand, the macroscopic model is identified by three parameters: flow, speed, and density [5], [6]. Fruin's first works in that field analyzed the relationship between macroscopic variables such as flow density and velocity as pedestrian characteristics in urban areas [7]. Sukhadia *et al.* [8] have studied the effect of events on pedestrian behavior analyzing pedestrian flow, walking speed, density, and space using regression analysis. Also at signalized intersections, researchers studied pedestrian behavior by quantifying some attributes like road and crosswalk width, gender, bidirectional flow, crossing time, also pedestrian characteristics as male-female-child. The observed data flow is plotted and the scattered diagrams follow Greenberg's logarithmic model [9]. Also, Muley *et al.* [10] have studied pedestrian crossing speed at signalized intersections using traffic analyzer software, the results show a correlation between speed and crosswalk length in red and green indications but pedestrian exit speeds were independent of crosswalk length. Another study perspective is pedestrian crowd modeling such as a macroscopic model, where pedestrians are subject to the laws of gas flow. In many studies, authors attempt to describe pedestrian mobility and behavior. Windyani *et al.* [11] propose the Lax-Wendroff scheme for conservation laws, describing velocity-density relation using linear regression, they verify the pedestrian flow conservation according to the two equations that describe the velocity as a function of density. In other studies, researchers describe fast exit scenarios in pedestrian crowds, using the Hughes model and mean field game with nonlinear mobilities [12].

In our study, we proceed to the modeling and prediction of pedestrian flow in a commercial avenue. In the literature, there are 3 ways of forecasting methods: statistical models, machine learning-based models, and deep learning-based models. Previous studies reported in the literature review propose prediction algorithms to forecast pedestrian flow.

Davis *et al.* [13] determine how can hourly flow be predicted based on short counting intervals using linear regression, where the middle interval position event produced the best model regardless of the size of the count interval. Bargegol *et al.* [14] use regression analysis to determine the relationship between space mean speed, flow rate, and density of pedestrians, in addition, the authors model pedestrian density using genetic algorithm (GP) as an optimization algorithm. In another study, Fujimoto *et al.* [15] aim to investigate the relationship between the spatial condition and crowd walk nature using regression analysis. Liebig *et al.* [16] use Gaussian process regression with diffusion kernel including topological information to estimate pedestrian mobility volume and how trajectory patterns improve traffic prediction accuracy. Zhang *et al.* [17] analyze pedestrian crowd density and speed using data from cellular operators through a hybrid model, the log distance path loss (LDPL), and the Gaussian process GP with supervised learning for modeling, regression, and prediction. Zhao *et al.* [18] use an artificial neural network to model and predict pedestrian unidirectional and bidirectional flow, this model is based on 2 sub models, semicircular forward space-based (SFSB) to learn magnitude and rectangular forward space-based (RFSB) to learn direction velocity. Tordeux *et al.* [19] evaluate pedestrian prediction flow in complex geometries (corridor and bottleneck) feedforward neural network (single hidden layer H=3 with 3 nodes) compared with the Wieldman model, where the first shows the best results. Cohen and Dalyot [20] developed an artificial neural network model to predict pedestrian traffic flow levels. Cohen and Dalyot [21] implement 6 machine learning algorithms (artificial neural network, support vector machine, stochastic gradient descent, AdaBoost, decision tree, and random forest) to model the correlation between the spatial features, road network structure, and pedestrian traffic flow, such that random forest algorithm shows the best results. Luca *et al.* [22] investigate deep learning algorithms to predict crowd pedestrian flow and compare them with classic time-series models based on autoregression such as autoregressive integrated moving average (ARIMA). Liu *et al.* [23] developed a model to predict the crowd flow in a walking street using the graph convolutional network (GCN) model and compared GCN with baseline methods (historical average, autoregressive integrated moving average, support vector machine, convolutional neural network, long short-term memory and spatio-temporal convolutional network) to validate the performance of pedestrian flow prediction. Angel *et al.* [24] use the decision tree regressor algorithm to identify the association between walkway volume and built environment features.

Tangier city has experienced a spectacular leap in urbanization and population growth [25], and in the last decade has become the second economic hub of Morocco. So, this is accompanied by increased urban mobility, both vehicular and pedestrian. This article studies bi-directional pedestrian flow in a commercial avenue in Tangier. The dimensions of the avenue are as follows: the pedestrian sidewalk width is 7 meters and 7 meters width for cars where 3 meters are for parking, as illustrated in Figure 1(a), according to direct observations, high congestion at the pedestrian level is noted. Since the dimensions of the avenue do not change, it is interesting to know how the pedestrian flow will evolve in the future, evaluating the walkway's ability to sustain an adequate level of pedestrians and help decision-makers to propose operational solutions. As a study methodology, we model and predict bidirectional pedestrian traffic flow. For this purpose, we use artificial neural network (ANN) and support vector machine (SVM) machine learning models, making a comparison between the two algorithms that best predict the flow. As a result, ANN gives a little better performance and fitness compared to the support vector regression (SVR) algorithm. This work would be the first attempt to study pedestrian flow in Tangier city by applying machine learning algorithms (no study has been established so far in that sense).

The work will be divided as follows: an introduction presenting the research objective, studies carried out in this sense, limitations, and our contribution. Then a second section explains the method followed, this section in turn divided into 2 sections, the data collection procedure and data processing through artificial neural network and support vector regression. A third section presents the results obtained, comparing the two algorithms through root mean squared error (RMSE) and R^2(determination coefficient), and finally a conclusion.

2. METHOD

This article aims to model and predict pedestrian traffic flow on sidewalks in commercial avenue, considering data collected in Tangier city (Morocco). The steps followed for this are detailed in the following sections. These stages can be summarized in two essential points.

- Data collection: Pedestrian flow and avenue geometry.
- Model and pedestrian flow prediction: Data analysis applying ANN and SVR. Comparing ANN and SVR results using root mean squared error (RMSE) and R^2 (determination coefficient).

2.1. Data collection

2.1.1. Study area selection

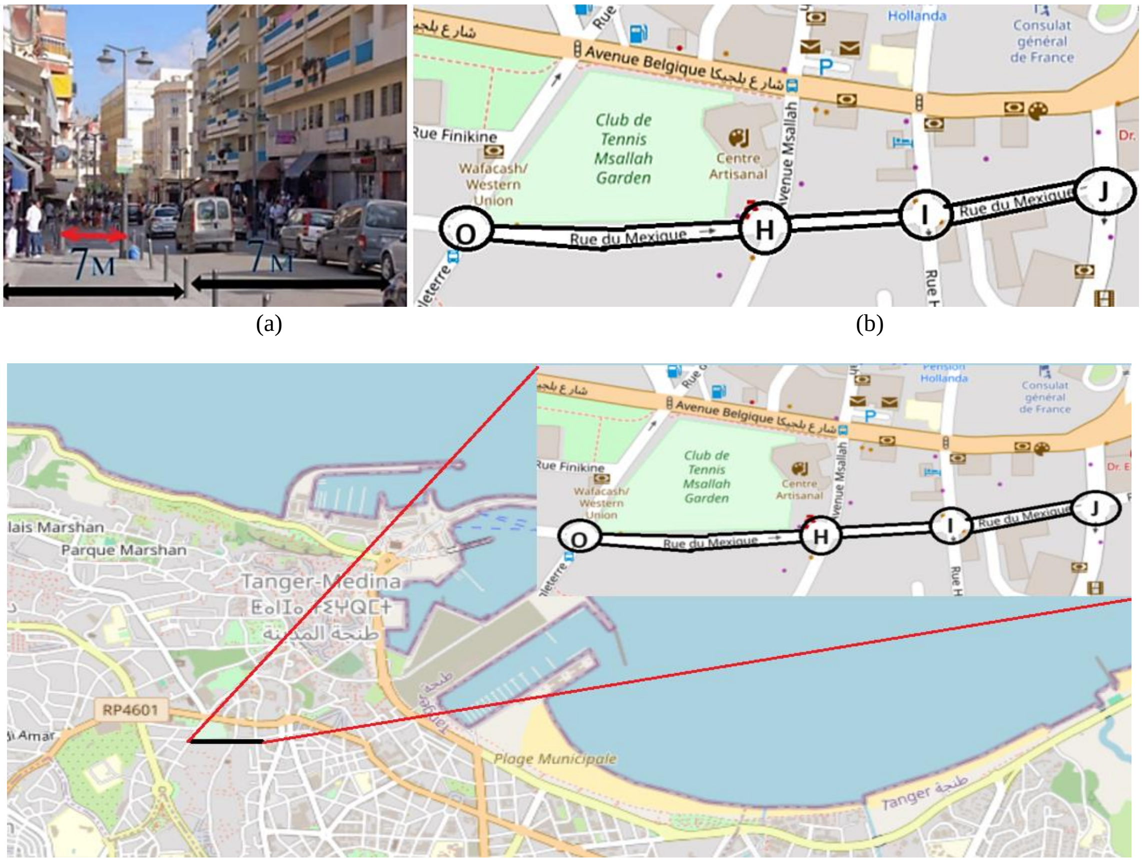
In this study, we chose a commercial avenue in Tangier city to analyze the pedestrian flow. The principal criterion for site selection was land use (commercial and entertainment), analyzing a mixed population of employees, shoppers, and visitors. The study area (Mexique avenue), as depicted in Figure 1(a), is located in the center of the city. With more than 85 stores and 14 shopping centers, it is a catchment area with high pedestrian movement. As shown in Figure 1(a), the sidewalk width is 7 meters, but the effective width has an average of 3 meters. Also, the presence of vehicles, makes pedestrian mobility difficult.

2.1.2. Procedure of data collection

Data collection must follow a well-structured methodology to avoid repeating fieldwork. First, we use a map to locate the area to be studied (using OpenStreetMap), then we proceed to model the area with a graph, identified by nodes (intersection of avenues in this case O, H, I, and J) and segments (avenues, in this case, OH, HI, IJ), as depicted in Figure 1(b), and finally, Figure 1(c) describes the location of the avenue on the map of Tangier city. The data collection refers to the bidirectional pedestrian flow/min using video recording, during a week divided into 7 intervals/day and making 15 measurements/section/interval, the time intervals are: 7h45-8h15, 9h45-10h15, 11h45-12h15, 13h45-14h15, 15h45-16h15, 17h45-18h45, 19h45-20h15. For each segment, 735 measurements are obtained for each week/month and during two months (June and November, to take into account the weather, according to the month).

2.2. Data analysis

Pedestrian network traffic data are nonlinear; therefore, machine learning (ML) algorithms (supervised learning, unsupervised learning, and reinforcement learning) are very appropriate for making predictions and identifying patterns automatically. ML is a subcategory of artificial intelligence in which computers imitate human learning, through the extraction of knowledge about unobserved properties of an object based on the properties that have been observed. Encompasses many types of problems, classification, ranking, and regression. Some of the best-known ML algorithms are decision tree, Bayesian networks, support vector machine, and artificial neural network. in this article, we use neural networks and SVR, and their proven effectiveness in forecasting tasks [26].



(a) (b)

(c)

Figure 1. Study area, (a) overview of the avenue, (b) avenue model, and (c) avenue location

2.2.1. Support vector machine

Support vector machines (SVM) are a set of supervised learning algorithms developed by Vapnik and Cortes in 1995 [27]. Their good performance led to their use to solve a large variety of classification (SVM) and regression (SVR) problems for linear and non-linear data (we can transform to linear data using kernel function). The SVR algorithm is based on finding the hyperplane that models the trend of the training data and based on it predicting any data in the future, the main idea is always the same: minimize the error. Based on a set of training sample $\{x_i, d_i\}$ with $i = 1, \dots, N$ the regression function that can approximate the output expressed by (1).

$$d = w^T x + b \tag{1}$$

The coefficients, vector w and bias b, estimated by resolving a quadratic programming problem, the objective function explained by (2) under the two conditions, expressed through (3) and (4):

$$Minimize\ \frac{1}{2}\|w\|^2 + C.\sum_{i=1}^{N}|y_i - d_i|_\varepsilon \tag{2}$$

Subject to:

$$d_i - y_i \leq \varepsilon + \delta_i \qquad \delta_i \geq 0 \tag{3}$$

$$y_i - d \leq \varepsilon + \delta^*{}_i \qquad \delta^*{}_i \geq 0 \tag{4}$$

where $|y_i - d_i|_\varepsilon$ the ε-insensitive loss function (training error). The constant C determine the tradeoff between the training error and the penalizing term $\|w\|^2$. The y_i is the estimator output produced in response to the input example x_i. The parameter ε represent the hyperplane marge. The prameters δ_i and $\delta^*{}_i$ slack variables that describes the loss function.

To solve this optimization problem, we construct a Lagrangian function $J()$, (5):

$$Minimize\, J(w,\delta_i,\delta^*{}_i,\alpha,\alpha^*,\beta,\beta^*) = \frac{1}{2}\|w\|^2 + C.\sum_{i=1}^{N}(\delta_i+\delta^*{}_i) - \sum_{i=1}^{N}(\delta_i\beta_i+\delta^*{}_i\beta_i{}^*) - \sum_{i=1}^{N}\alpha_i(w^Tx+b-d_i+\varepsilon+\delta_i) - \sum_{i=1}^{N}\alpha^*{}_i(d_i-w^Tx-b+\varepsilon+\delta^*{}_i) \quad (5)$$

$\alpha,\alpha^*,\beta,\beta^*$ is Lagrange multipliers. Carrying out this optimization, we obtain (6), (7), and (8).

$$\widehat{w} = \sum_{i=1}^{N}(\alpha_i-\alpha^*{}_i)x \quad (6)$$

$$\alpha_i+\beta_i = C \quad (7)$$

$$\alpha^*{}_i+\beta_i = C \quad (8)$$

All the constraints that are not satisfied as equalities, the corresponding variables of the dual problem, expressed by the objective function described by (9), subject to (10).

$$\text{Maximize} \sum_{i=1}^{N}(\alpha_i-\alpha^*{}_i)\,d_i - \sum_{i=1}^{N}(\alpha_i-\alpha^*{}_i)\varepsilon - \sum_{i,j=1}^{N}(\alpha_i-\alpha^*{}_i)(\alpha_j-\alpha^*{}_j)K(x_i,x_j) \quad (9)$$

Subject to:

$$\sum_{i=1}^{N}(\alpha_i-\alpha^*{}_i) = 0 \quad 0 \le \alpha_i,\alpha^*{}_i \le C \quad (10)$$

Finally, the nonlinear function, (11) is obtained as:

$$d = \sum_{i=1}^{N}(\alpha_i-\alpha^*{}_i)K(x_i,x_j) + b \quad (11)$$

where $K(x_i,x_j)$ is defined as the kernel function. Any function that satisfies Mercer's theorem can be used as the kernel function (sigmoidal, linear, radial basis) [28]. In this research, the parameters used to show the best results are: radial basis kernel function, $C = 100$, $epsilon = 0$ and $gamma = 0$ (RBF parameter). Gaussian radial basis function, detailed in (13):

$$K(x_i,x_j) = \exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right) \quad (12)$$

2.2.2. Artificial neural network

An artificial neural network (ANN) is a mathematical model that attempts to imitate the functioning of the human brain, as shown in Figure 2. According to the network topology, we can differentiate between feedforward, back forward, and recurrent. Neural networks or perceptron (supervised learning with multilayer perceptron (MLP)), as represented in Figure 1, are the most used, extending their application to almost all technical areas. The main elements are network structure, activation functions (Sigmoid, Gaussian, Linear, ...), and learning algorithm (consists of all network parameters adjustment) [29].

Learning is an iterative process starting from a set of random weights, learning seeks a set of weights that allows the ANN to develop a specific task (forward propagation). MLP networks use an error function that measures their current performance, based on their weights (error estimation). Learning becomes a process of searching for those weights that make said function minimal (backward propagation, using gradient descent, backpropagation, quasi-Newton, Levenberg-Marquardt). These training processes will be repeated a certain number of times (Epochs), to adjust the value of the different parameters of our network [30]. We can summarize the algorithm in the following steps, testing and training.

a. Forward propagation, model result (output y_t), expressed by (12):

$$y_t = W_0 + \sum_{j=1}^{q} W_j.f\left(W_{0j} + \sum_{i=1}^{p} W_{ij}.y_{t-i}\right) \quad (12)$$

   where W: weights, $f()$: activation function, output, y_{t-i}: inputs.

b. Error estimation, expressed in (13):

$$E = \frac{1}{N}.\sum_{n=1}^{N}(y_t - (W_0 + \sum_{j=1}^{R} W_j.f(W_{0j} + \sum_{i=1}^{p} W_{ij}.y_{t-i})))^2 \quad (13)$$

where E is cost function.

c. Backward propagation, updating weights to minimize the error function (cost), as expressed in (14):

$$W(n+1) = W(n) - \alpha.\Delta E(w) \quad (14)$$

where α is learning rate and $\Delta E(w)$ is gradient of cost function.

For our ANN model, one feedforward, the number of hidden layers is one, with 10 neurons and the number of epochs is fixed on 1,000, and the network is trained with the Levenberg–Marquardt algorithm to minimize functions and allow fast convergence.

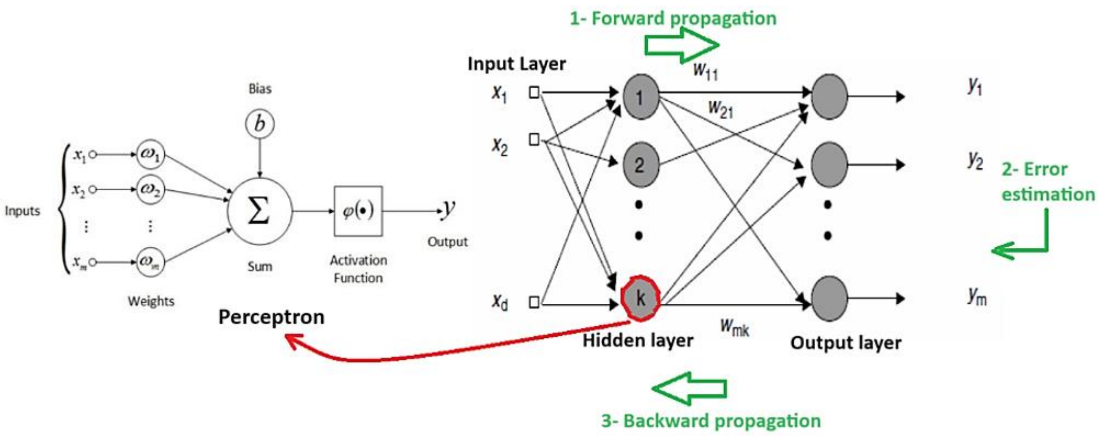


Figure 2. Architecture neural network model

2.2.3. Data description and treatment

The input data of each segment is a matrix of the month, day, time, and the number of pedestrians in the previous segment. The output vector is a vector of the pedestrian's flow for a given month – day and time. The variables are encoded as follows: our input data is a matrix of month, day, and time. Each element of this matrix is expressed as:

- For the month we consider the values of 1, 2, …, 12 to identify the months, January, February, … December
- For the day we used the numbers 1, 2, …, 7 to identify Monday …., Sunday
- For hours, we can express through (15):

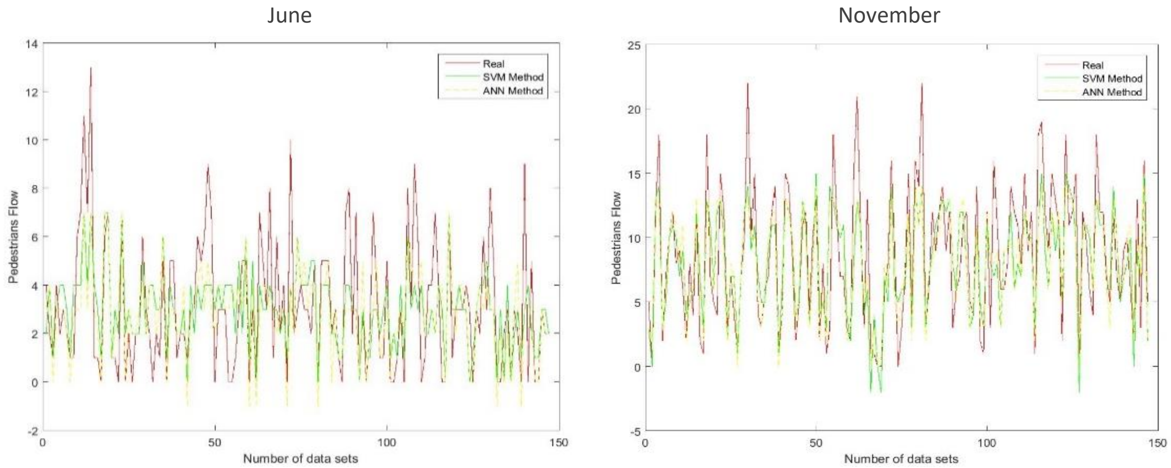
$$Time = \frac{hours + \frac{minutes}{60}}{24} \quad (15)$$

For each segment, 735 measurements are obtained each week/month and during two months (June and November).

3. RESULTS AND DISCUSSION

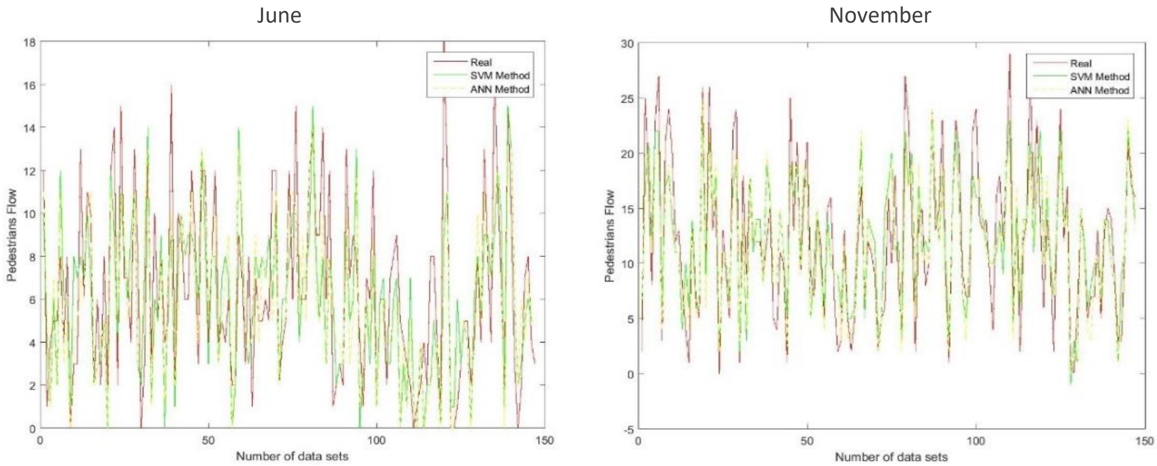
In our simulations, 80% of the data was used as input to SVR and ANN models (training data) and the remaining 20% is intended to test the model (testing data). In Figures 3, 4, and 5 we exhibit the simulation results of pedestrian's flow, real data, and prediction of every segment in Mexique Avenue, OH, HI, IJ, using SVR and ANN methods for two months June and November. Figure 3 shows the simulation result (comparison between the real result of pedestrian flow, ANN model, and SVR model) of the OH segment, where Figure 3(a) shows the result for June, while Figure 3(b) shows the simulation results for November. Figure 4 shows the HI segment's simulation result (comparison between the real result of pedestrian flow, ANN model, and SVR model). Figure 4(a) shows the result for June, while Figure 4(b) shows the simulation results for November. It can be seen in the results that the two algorithms ANN and SVR adequately simulate the real pedestrian flow.

Figure 5 shows the IJ segment's simulation result (comparison between the real result of pedestrian flow, ANN model, and SVR model). Figure 5(a) shows the result for June, while Figure 5(b) shows the simulation results for November. It is observed that the two algorithms ANN and SVR adequately simulate the real pedestrian flow.



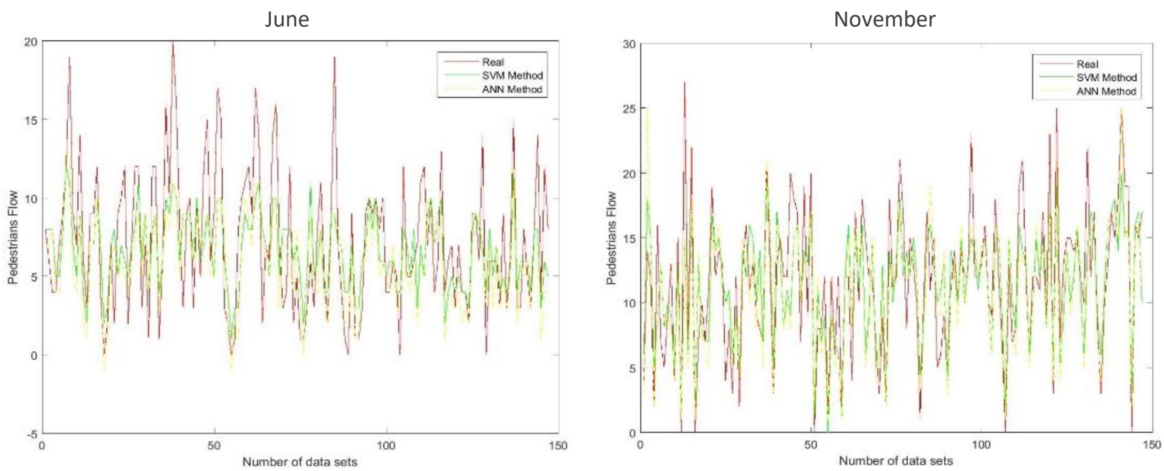
(a) (b)

Figure 3. Simulation results for OH segment, (a) June and (b) November



(a) (b)

Figure 4. Simulation results for HI segment, (a) June and (b) November



(a) (b)

Figure 5. Simulation results for IJ segment, (a) June and (b) November

Two performance criteria were used to evaluate the prediction ability of the SVR and ANN model, as shown in Tables 1 and 2, including determination coefficient R^2 and RMSE, explained by (16) and (17) respectively. We use these two metrics to assess prediction results and the simulation's effectiveness.

$$R^2 = \frac{\sum_{i=1}^{N}(\hat{Y}_i-\bar{Y})^2}{\sum_{i=1}^{N}(Y_i-\bar{Y})^2} \quad (16)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{Y}_i - y_i)^2} \quad (17)$$

The RMSE is considered an excellent error metric and represents the sample standard deviation of the differences between predicted values and observed values of pedestrian flow. The determination coefficient R^2 represents how well the forecasting model explains the collected data (shows the goodness of fit for regression models), where $\hat{Y}_i$, y_i, and $\bar{Y}$ denotes the estimated, observed and the average of y_i values respectively. N represents the number of samples for prediction.

Table 1. RMSE values for SVR and ANN algorithms for every segment of Mexique avenue

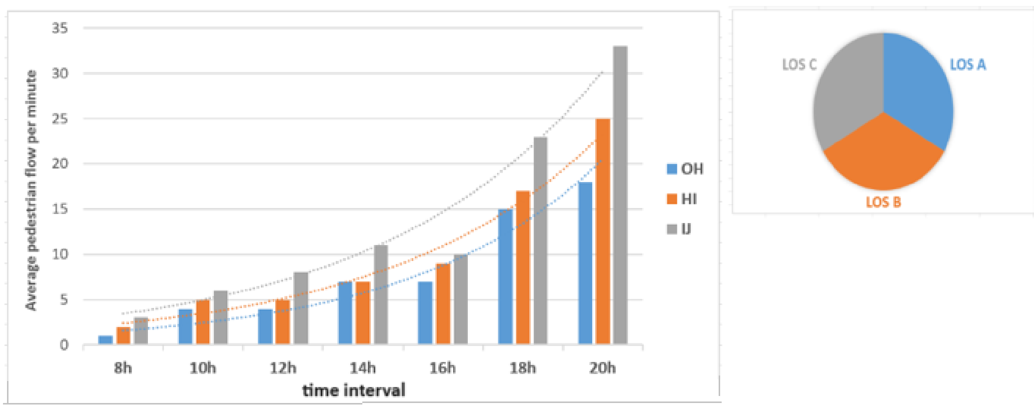
	OH	HI	IJ
RMSE - SVR	2.59	3.24	3.24
RMSE - ANN	2.49	3.03	3.29

Table 2. R^2 values for SVR and ANN algorithms for every segment of Mexique avenue

	OH	HI	IJ
R^2 - SVR	0.70	0.71	0.61
R^2 - ANN	0.71	0.74	0.60

According to Tables 1 and 2, the average value of each performance criterion shows it can be observed from the estimated R^2 and RMSE values, that both SVR and ANN could be used to model and simulate pedestrian flow. ANN gives a little better performance and fitness compared to the SVR algorithm. The preparation of this work had two essential objectives, the first is to model the pedestrian flow in a commercial avenue, and this has a direct impact on the possibilities of future congestion of this avenue. The second objective is the comparison between ANN and SVR, with ANN having been the object of study in several scientific articles on the modeling and prediction of pedestrian flow and which has proven to be a good model for the simulation of the pedestrian flow. Moreover, SVR method according to the literature, there are not many works that have used this method as a prediction or simulation model of pedestrian flow but it is used in traffic flow (vehicular) modeling, and the simulation results show good results.

According to simulation results indicated in Figures 3, 4, and 5 the ANN and SVR models simulate adequately the real pedestrian flow. The findings indicate that the proposed models are reasonable and capable of simulating and predicting pedestrian flow. If we resort to a descriptive analysis of the average pedestrian flow along the three segments of the avenue and consider the 7 intervals of the day, during June and November, as shown in Figure 6(a). Figure 6(b) indicates the level of service in the avenue according to the highway capacity manual (HCM) guide [31].



(a) (b)

Figure 6. Descriptive analysis of pedestrian flow, (a) average pedestrian flow per minute in each segment, and (b) PLOS, pedestrian level of service in the avenue

In Figure 6(a), the result shows that the pedestrian flow increases progressively, from the first interval 7h45-8h15 to the last interval 19h45-20h15, in the three segments. Furthermore, the flow increases significantly from the intervals 17h45-18h15 to 19h45-20h15. It is also noted that the pedestrian flow is higher in the two segments HI and IJ than in the OH segment. Figure 6(b), describes the pedestrian level of service (PLOS) in this avenue. PLOS is a measure that quantifies walkway comfort levels, defined into six categories (A, B, C, D, E, F) each level defines the range of values, for example, a good level (best traffic condition) is defined with the letter A until reaching the worst level, F (high congestion). According to the result obtained, LOS A=33.33%, LOS B=33.33% and LOS C=33.33%. The result distribution is equitable, LOS C, it is due to the increase in flow in the hourly interval 19h45-20h15.

4. CONCLUSION

Mobility plans are one of the most important management tools for city development and an important factor for society and economic growth. Pedestrians are the end goal of any mobility plan. We have found through the literature, that pedestrian behavior has been studied by several authors, and by different perspectives, social and mathematical modeling. In this work, we have studied pedestrian mobility in a commercial avenue of Tangier city. This study has concentrated on the pedestrian flow model. The data collection process has been developed through the implementation of a methodology to facilitate and optimize the process. we have developed two prediction models based on machine learning algorithms ANN and SVR. The results show that ANN gives a little better performance and fitness compared to the SVR algorithm, using determination coefficient R^2 and RMSE. The analysis of pedestrian flow reveals the ability of both methods SVR and ANN to predict the number of pedestrians in different parts of time. We can use this result as a decision tool to improve pedestrian mobility in this area, such as pedestrianization of the avenue.

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BIOGRAPHIES OF AUTHORS

Marwane Benhadou is an assistant professor of informatics, at Abdelmalek Essaâdi University. His research interests include telecommunications, mathematical modeling and computing, traffic engineering, and sustainable mobility. He can be contacted at email: marwane.feg.info@gmail.com.

Amina El Gonnouni received a computer science degree from the Science and Technology Department, Abdelmalek Essaadi University, Tangier, Morocco, the D.E.S.A. degree in telecommunications systems from the Faculty of Science of Tetouan, Morocco, and the Ph.D. degree in telecommunications and informatics from the Faculty of Science of Tetouan, Morocco. Her research interests include artificial intelligence, machine learning, and statistical learning for signal processing, cognitive radio, and sensor networks. She can be contacted at email: amina_elgo@yahoo.fr.

Abdelouahid Lyhyaoui is a full professor at the National School of Applied Sciences of Tangier. He holds the PhD degree in telecommunications engineering from the Escuela Politecnica Superior, Universidad Carlos III de Madrid. His research interests include data science, artificial intelligence, and smart cities. He has participated in several national and international research projects and has more than 150 scientific publications. He is a member of scientific committees of several national and international conferences and journals. director of the Innovative Technologies Laboratory, elected member of the Scientific Council, the Board of Directors, the Pedagogical Commission of the University. He can be contacted at email: lyhyaoui@gmail.com.