World Academy of Science, Engineering and Technology
International Journal of Urban and Civil Engineering
Vol:16, No:7, 2022

Time Organization for Urban Mobility Decongestion: A Methodology for People's Profile Identification

Yassamina Berkane, Leïla Kloul, Yoann Demoli

Abstract—Quality of life, environmental impact, congestion of mobility means, and infrastructures remain significant challenges for urban mobility. Solutions like car sharing, spatial redesign, eCommerce, and autonomous vehicles will likely increase the unit veh-km and the density of cars in urban traffic, thus reducing congestion. However, the impact of such solutions is not clear for researchers. Congestion arises from growing populations that must travel greater distances to arrive at similar locations (e.g., workplaces, schools) during the same time frame (e.g., rush hours). This paper first reviews the research and application cases of urban congestion methods through recent years. Rethinking the question of time, it then investigates people's willingness and flexibility to adapt their arrival and departure times from workplaces. We use neural networks and methods of supervised learning to apply a methodology for predicting peoples' intentions from their responses in a questionnaire. We created and distributed a questionnaire to more than 50 companies in the Paris suburb. Obtained results illustrate that our methodology can predict peoples' intentions to reschedule their activities (work, study, commerce, etc.).

Keywords—Urban mobility, decongestion, machine learning, neural network.

I. Introduction

CONGESTION has been a significant problem for cities around the world. Clearly, solutions for this problem require rethinking the time and spatial questions of the concerned territories.

Rethinking the spatial question is a complex and intricate public policy issue because it requires redesigning the road infrastructure (highways, streets,..). Moreover, aspects such as network plan, geometric design, traffic control, operation, regulation and enforcement of roads must be considered as a unified system [1]. In this study we are interested in time rethinking by suggesting temporalities to users in urban areas. This question is the primary mission entrusted to time offices in several European urban areas. This mission consists of acting on the causes of mobility congestion at certain day times by rethinking the activities' schedules (work, study, commerce, etc). However, this schedule reconsideration cannot be achieved without considering all the activities and resources constraints (not only the ones linked to mobility) and the characteristics of the impacted populations. For example, we cannot suggest that a couple who has children should start working at 8:00 AM, knowing they have to drop off their children at school before work. Another example involves coordinating the start and end times of university classes with those of public transport. Such a coordination requires taking into account not only the availability of transportation but also the availability of the educational resources (classrooms, teaching and security staff, ...). More importantly, this requires considering the sociology of the students and teachers (age, address, and family situation). Likewise, thinking about diversified working hours requires coming back to the relationship of individuals to the work and the way they articulate professional activity and private life.

In this paper, we investigate people's willingness and flexibility to adapt their arrival and departure times from their workplaces to reduce urban mobility congestion. For that we propose a methodology for people's profile identification. This methodology consists first in a data collection and analysis of a survey distributed to employees of more than 50 companies in Grand Paris Sud suburb area. In the second step of this methodology, we define three classes of mobility profiles (*Unfavorable*, *Favorable flexible*, and *Favorable not flexible*), according to the persons' willingness and flexibility to adapt their arrival and departure times from workplaces. These profiles classes are predefined using a set of sociological criteria. In the last step, we use supervised machine learning techniques to analyze the survey data in order to predict the profile of the employees according to the predefined classes. The obtained results show that our methodology can predict well individual profile in terms of mobility.

Structure of the paper: in Section II, we discuss related work. Section III is dedicated to the proposed methodology for mobility profiles identification. In Section IV, we discuss the content of the distributed questionnaire and the criteria that we fixed. Section V gives a brief overview of the selected machine learning techniques used while Section VI describes the application of these techniques. Section VII summarizes and discusses the obtained results. The last section is dedicated to our conclusions and suggestions for further research.

II. Related Work

Integrating autonomous vehicles is one of the most promising solutions to reduce congestion. An AV (autonomous vehicle) takes the same road space as a conventional vehicle of similar capacity, but it wields power to operate at reduced

Y. Berkane and L. Kloul are with DAVID Laboratory, Université de Versailles Saint-Quentin-en-Yvelines, Versailles, France (e-mail: yassamina.berkane@uvsq.fr, leila.kloul@uvsq.fr).

Y. Demoli is with PRINTEMPS Laboratory, Université de Versailles Saint-Quentin-en-Yvelines, Versailles, France (e-mail: yoann.demoli@uvsq.fr).

headways on narrower lanes. This novel feature thus increases road capacity and consequently reduces traffic congestion. An AV can also indirectly impact congestion by reducing the need for cars to park in or near the workplace; for example, a driverless vehicle can return home after dropping off the owner. However, this solution could extend the use of cars to those who are not able or qualified to drive (children, the elderly, and people with disabilities), worsening congestion [2].

Car sharing is a term used for a business model where the user is not a passenger but a driver who shares the car. It could be operated by companies or organizations that provide numerous vehicles for their members to share [3]. Car sharing and carpooling also present a possible solution due to increasing car occupancy. However, reduced congestion would attract potential road users [4]. Additionally, lower costs associated with shared use might attract public transport passengers, thus increasing the demand for cars and taxis [2]. The effect of shared-use vehicles on congestion is not apparent and is similar to connected vehicles.

Connected vehicles refer to applications, services, and technologies that connect a vehicle to its surroundings [5]. Due to their adaptive cruise control, connected vehicles adjust the distance between nearby vehicles using sensor data [2].

Another exciting technique is the deployment of Autonomous Mobility on Demand (AMOD). The challenge of such AMOD systems is to ensure the availability of transport in travel while removing the need to own a car. However, this objective faces a significant problem concerning the imbalance of the distribution of vehicles. A re-balance that leads to crossing the same, or greater distances must be made [6], [7].

Congestion pricing is another potentially effective solution to reducing traffic congestion cited in the literature. However, we do not know how acceptable this solution would be for travelers [8]. We consider the following example in Gothenburg, Sweden, where traffic jams decreased by 12% between $2013-2015$. During these years, the city established 37 toll booths surrounding the city center, but the citizens refused to pay the appropriate fines after one year.

None of the studies cited above consider the sociology of people who adapt their working hours to reduce congestion. Each solution proposed eventually develops a novel problem following its implementation.

III. Methodology

The objective of this paper is to investigate a systemic and interdisciplinary approach which allows us to have a better understanding of the urban mobility. This approach includes concepts from both computer science, and human and social science. It relies on the 3-steps methodology depicted in Fig. 1.

The first step of our methodology consists of data collection. For that we launched a questionnaire to have the individuals' opinions and expectations regarding their mobility and work organization. Using some specific questions from the questionnaire, in the second step of the methodology,

Fig. 1 The 3-steps methodology

we define a set of sociological criteria which rely on the sociological profile, and the personal and professional constraints of the surveyed persons. The combination of these criteria allows us to predefine and characterize the individuals' profiles (classes) we use during the last step of our methodology, where we apply machine learning technique on the collected data in order to predict the profile of the surveyed persons. Each of these steps is detailed in the following subsections.

A. The Questionnaire

The questionnaire has been defined in collaboration with Ile-de-France Region and Grand Paris Sud Urban Community. It was distributed to the employees of more than 50 companies in the Paris suburb area between May and October 2021. This questionnaire deals with the evolution of the mobility and the work organization before and after the sanitary crisis. It consists of the following four main sections.

1) Mobility and work organization before the health crisis: This section includes questions about the transport mode used by the employees to travel to their workplace and its frequency. It also questions about how pleasant this journey is for these employees and what are, in their opinion, the most important criteria for a pleasant journey, as well as the ideal transport mode to use. Further questions concern the journey times, the distances traveled between their homes and workplaces, the usual arrival time at the workplace, and the reasons behind it. A final part deals with the issue of teleworking before the sanitary crisis.

2) Mobility since the health crisis: This section includes questions about the transport mode used and its frequency. It also contains questions about the wish of the employees to change their transport mode and the reasons behind this wish.

3) The organization of work since the health crisis: This part discusses how employees worked during the sanitary crisis, particularly during the three first phases of confinement. Other questions are related to their satisfaction with the terms and conditions of the work organization set by their company.

4) Personal information about the respondents: This last section contains questions about personal information of the surveyed persons (gender, age, marital and family situation, socio-professional categories, etc.). These information are necessary to identify the possible scenarios of work

temporalities that can be proposed to them, taking into account their socio-logical profile.

B. Criteria for Profile Prediction

In this study, a person's profile can be determined according to her/his willingness and flexibility to change her/his start work time and off-work time in order to reduce traffic congestion. Accordingly, we consider that a person can belong to one of the following profiles:

- *Unfavorable (UNF)*: This profile concerns persons who are happy with their current work organization and therefore do not want any changes.
- *Favorable flexible (F-F)*: These are employees who are in favor for changes in their current work organization and are flexible because they have no personal constraints.
- *Favorable not flexible (F-NF)*: This profile groups persons who are in favor of changes but because of personal constraints are not flexible.

To be able to predict the profile of a person, we need to characterize each of the predefined profile. For that, for each type of profile, we associated a set of appropriate criteria that have to be satisfied by a person to belong to this profile. The satisfaction of a criterion depends on the answer(s) given to one or more questions in the questionnaire.

Fig. 2 summarizes the defined criteria. As we can see, the first criterion we consider is *Work organization*. To the question *"When you return to your workplace, what would you like to change in your current work organization?"* the person must answer *"Nothing, the current organization suits me"* and *"No change desired in my work organization"* to say that she/he is not in favor of changes in her/his work organization, that is the shift of her/his working hours. This person will be classified as *Unfavorable (UNF)*.

In the case where the person does not respond by these answers, we need to investigate her/his answers to other questions in the questionnaire. This investigation allows us to check if the criteria provided in box A or box B are verified (see Fig. 2). We consider that three out of four of them $(3/4)$ must be satisfied to say whether the person is in favor (box A) or not (box B) for the shift of her/his working hours.

If a person is considered as in favor of changes in her/his work organization, the second processing step consists of predicting whether this person is flexible or not. For that, we set two criteria: *having dependent children* and *having strong personal organizational constraints*. If a person satisfies both criteria then that person is considered as *Favorable not flexible (F-NF)*. In revenge if, at least, one of these criteria is not satisfied then the person is considered as *Favorable flexible (F-F)*.

Given that the questions corresponding to the criteria entries are multiple-choice, we can have two or more set of answers belonging to two categories at the same time. For that we set a priority order as follows: *UNF*, *F-F*, *F-NF*. For example, if a person answers the question: *"Why do you want these changes in your work organization?"* by both statements *"I would be more efficient and productive"* which is a response corresponding to an *F-F* profile, and *"It will be good for my work-life balance"* which is a response which may correspond to an *F-NF* profile, we consider, using the priority order set, that this person has an *F-F* profile.

For the unknown cases, that is, persons which may not satisfy all the criteria and the conditions defined for each profile, we rely on the machine learning based prediction approach to predict to which category or profile these persons belong.

C. Machine Learning Techniques

In this study, we use two different machine learning methods to predict the profile of a person: Multi-Layer Perceptron (MLP) neural networks and K-Nearest Neighbors (KNN) method. Both techniques are based on supervised learning, and have been chosen for their applicability and ability to process the categorical data we are interested in.

1) MLP neural networks method: Artificial neural networks (ANN) have recently been rediscovered as an essential alternative to various standard classification methods. A good definition is given by Haykin, describing neural network as a massively parallel combination of the simple processing unit which can acquire knowledge from the environment through a learning process and store the knowledge in its connections [9]. In theory, a neural network can perform any given classification task, provided that a judicious choice of the model is made and a suitable training method is implemented [10].

MLP neural network is one of the most effective artificial neural network techniques for modeling and prediction. It is a feed-forward model comprising one input layer, one or more hidden layers, and one output layer. While the hidden layers are used for computation (see Fig. 3), the output layer represents the modeling purpose. In our case the output layer models the defined profiles.

Generally, the number of nodes composing the input layer depends on the selected factors in the data source, and the hidden layers nodes are quantified based on a specific training dataset. Using the network's connections, the training implementation of the MLP method can be divided into two stages: forward and backward propagations.

During the forward stage, the output values of the MLP neural network are calculated using the input data and the connections weights between the different layers. This computation process is given by function $f(X)$ below, where X is the input data vector, W_1 and W_2 are the matrices of the connections weights, and b_1 and b_2 are the bias vectors of the hidden and the output layer, respectively.

$$f(X) = b_2 + W_2 * f_A(b_1 + W_1 * X)$$

f_A represents an activation function. The most popular activation function is the sigmoid function. The weight matrices W_1 and W_2 as well as the bias vectors b_1 and b_2 are randomly initialized first and then updated through a training process. The training parameters such as learning rate and training epoch are set based on experience.

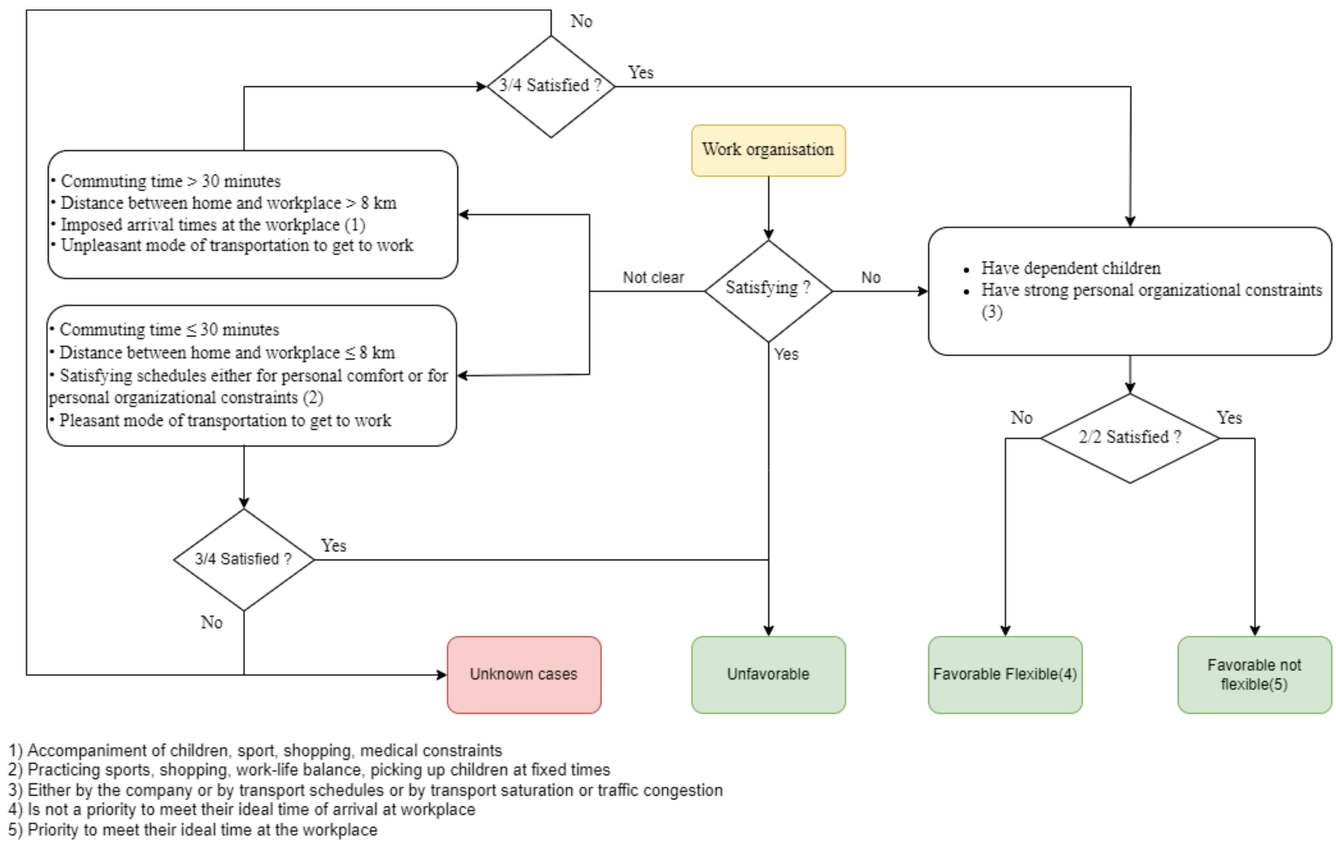

Fig. 2 Criteria for profile prediction

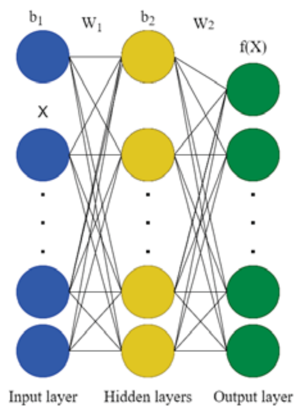

Fig. 3 An MLP with one hidden layer

Comparing the model's output values to the target values estimates the error value which can be minimized in the backward stage by updating the connection weights.

2) K-nearest neighbors method: The nearest neighbors algorithms are among the simplest of all machine learning algorithms. The idea is to memorize the training set and then predict the label of any new instance on the basis of the labels of its closest neighbors in the training set. KNN classification goes through two stages; the first one allows the determination of the nearest neighbors by calculating the Euclidean or Manhattan distance and the second one allows the determination of the class using those neighbors.

The KNN method is a non-parametric classification method, which is effective in many cases. However, it requires the selection of an appropriate value for parameter K, and the success of classification is very much dependent on this value. In a sense, the KNN method is biased by K [11]. A basic illustrative example is shown in Fig. 4. If we set $K = 3$, the new data to classify (the dot in green) will be classified as a triangle, but if we choose $K = 5$, it will be considered as a square. There are many ways of choosing the K value, but a simple one is to run the algorithm with different K values and choose the one with the best performance.

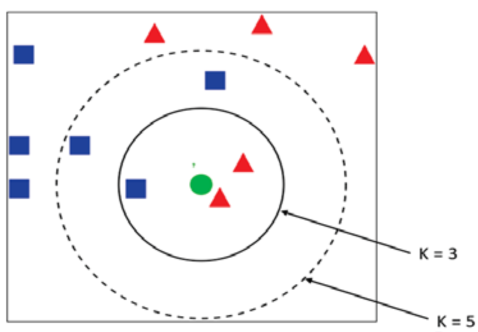

Fig. 4 K-nearest neighbors technique

IV. Profile Prediction Using Machine Learning Techniques

From the distributed questionnaire, we collected 1178 employees responses. 214 incomplete responses were omitted, leaving us with 964 responses, which is sufficient for a sample representative of the Grand Paris Sud suburb area.

Each sociological criterion we defined in Section III-B was associated with a set of questions. Thus, using the employees' responses, we have derived a dataset which consists of 16.258.032 possible sets of responses, of which 14.748.145 can belong to one of the predefined profiles and 1.509.887 are unknown. This dataset is first pre-processed before being used as input data for our machine learning models.

A. Data Pre-Processing Using One-Hot Encoding

The responses of the questionnaire are independent so we consider one-hot encoding as the coding scheme for the input data of our model.

One-hot encoding is the simplest way to mathematically represent the responses to every question and therefore, it is the most widely used coding scheme. One-hot encoding is a representation of categorical variables as binary vectors. Each question is represented as a binary vector where all values are zeros, except the index of the given response which is marked with 1. For instance, a question with N possible responses uses a vector of N dimensions to represent each answer to this question. This representation can work only with a single choice question. For multiple-choice questions (case of our questionnaire), we have to change the index position of every selected response to 1.

The input of the used machine learning methods has 28 hot encoded entries, corresponding to individual responses to all selected questions.

B. MLP Neural Network Parameters

Our MLP neural network consists of a 28-nodes input layer and one hidden layer of 42 nodes. Because of the number of profiles we have defined (3), the output layer consists of 3 nodes only. This network has a total of 1347 parameters, distributed as follows: 1218 parameters at the level of the hidden layer and 129 parameters in the output layer. The number of parameters in the hidden layer is obtained by considering the connections weights between the first two layers $(28 * 42)$ plus 42, the bias values of the hidden layer. Similarly, the number of parameters in the output layer is obtained by considering the connections weights between the last two layers $(42 * 3)$ and the bias values (3) of the output layer. Table I summarizes the parameters of our MLP neural network model.

TABLE I
Parameters of the MLP Neural Network

Layer(type)	Output shape	Parameters
Input layer	28	
Hidden layer	42	1218
Output layer	3	129
Total parameters: 1347		
Trainable parameters: 1347		
Non-trainable parameters: 0		

C. K-Nearest Neighbors Method Parameter

As explained before, the K-Nearest-Neighbors method is a simple and effective method for classification but which requires the setting of an appropriate value of parameter K. For that, we run the algorithm several times with different K values. This experimentation allowed us to select the best K value, that is the one that raises the smallest error value. According to this experimentation, $K = 13$ is the best value to consider in our case. The error value as a function of K value is plotted in Fig. 5.

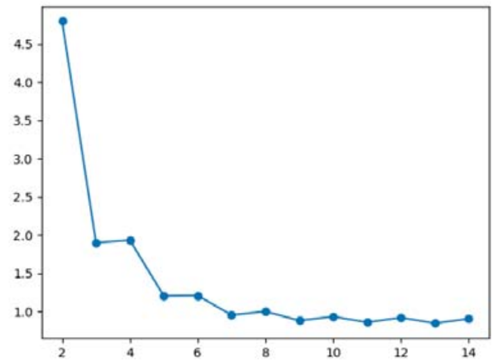

Fig. 5 Error value as a function of the parameter K value

V. Numerical Results

This section presents the numerical results obtained when applying the proposed methodology on the questionnaire data. During the training process, the model is trained with the data of 30% of the known cases. We evaluated the model using cross-validation technique with the remaining 70% of known cases. An accuracy of 97% is reached, which is an excellent score to consider our model as reliable.

A. MLP Neural Network Method

Applying MLP neural network method on the survey data classifies 531 persons as *Favorable flexible (F-F)* and 396 persons as *Unfavorable (UNF)*. Only a tiny proportion was considered as *Favorable not flexible (F-NF)*. On the 964 surveyed persons, this represents 55%, 41%, and 4%, respectively.

In order to identify the factors that impact this classification, we have analyzed these results considering the gender (female, male), the socio-professional category (SPC), the marital status, and having or not small children. The obtained results are presented in the following.

1) The Gender Impact: The distribution of profiles according to the gender is shown in Fig. 6. This figure shows that:

- A small proportion (1.33%) of people did not wish to say what gender they are.
- Among the 455 surveyed men, almost 40% are considered as *UNF* and 56.48% are not only favorable but also flexible (*F-F*). Similarly almost 43% of the 496 surveyed

Fig. 6 Neural network results according to the gender

women are considered as *UNF* and 53.62% as *F-F*. Thus, the *F-F* profile remains the majority for both women and men.

Clearly, according to the results obtained with the MLP model, there is a very small difference in the profiles according to gender. Thus, gender has little impact on the preferences for changing the start and end of working hours.

2) Impact of the Marital Status and the Presence of Children: Fig. 7 presents the distribution of profiles according to family situation (living with a partner or not) and whether they have dependent children or not. The y-axis displays the percentage of persons in each profile, and the x-axis shows the marital situation of the persons. We distinguish between persons having or not children with the first line of the bar (*no* for persons who do not have children, and *yes* for those who have). These results show that:

- Ten persons (1.14%) did not provide information on their marital status.
- 51% of single people with no dependent children are *F-F* and 49% are *UNF*.
- Men represent the majority of those who have personal and professional constraints, and thus are not *flexible* to change their working hours.
- The profile *F-NF* exclusively concerns people who live with a partner and have dependent children. For this category, the profile distribution according to the gender and the socio-professional category is detailed in the next point.

3) Impact of the Socio-Professional Category (SPC): Fig. 8 presents the distribution of people's profiles according to their SPC. These results show that:

- A considerable majority (57.78%) of the persons surveyed belongs to the third category of SPC ("Manager, intellectual professions"), according to the INSEE (The National Institute of Statistics and Economic Studies, abbreviated INSEE) classification in France. In this category, 334 persons (59.96%) are classified as *F-F*, 17 persons (3.05%) as $F-NF$, and 206 persons (36.98%) as *UNF* for changing their working hours.
- In the category of "Employees", 95 persons (47.98%) are classified as *F-F* and 90 (45.45%) as *UNF*.
- The majority of students are not in favor (*UNF*) of changes of their start and end working hours.

B. KNN Method

The aim of this section is, first, to present the results of a different machine learning method (KNN), and then to compare them by considering the same criteria as for the previous method. The processing delivers for the *KNN* method 552 *F-F* cases out of 964, against 403 *UNF* cases, and a tiny proportion of non-flexible favorable cases representing, respectively, 57%, 42%, and 1%.

1) The Gender Impact: A first analysis concerns the impact of gender on the classification of individuals. Fig. 9 describes the distribution of profiles obtained.

- We see that 59% of men are *F-F* against 54% of women, and 40% of men are *UNF* to change against 43% of women.
- Men are more favorable to change and women who are favorable are less flexible.
- There is a big similarity between the distributions of the three profiles as the difference in profiles (*UNF*, *F-F*, and *F-NF*) according to gender is not significant.

Thus, like with MLP neural network method, gender has little effect on the distribution of the profiles obtained using KNN method.

2) Impact of the Marital Status and the Presence of Children: A second analysis concerns the impact of the marital status (living with a partner or not) and the fact of having or not dependent children on the classification of individuals using KNN method. Fig. 10 shows the distribution of individuals' profiles obtained. We distinguish between people having children or not with the first line of the bar (*no* for people who do not have children, and *yes* for those who have).

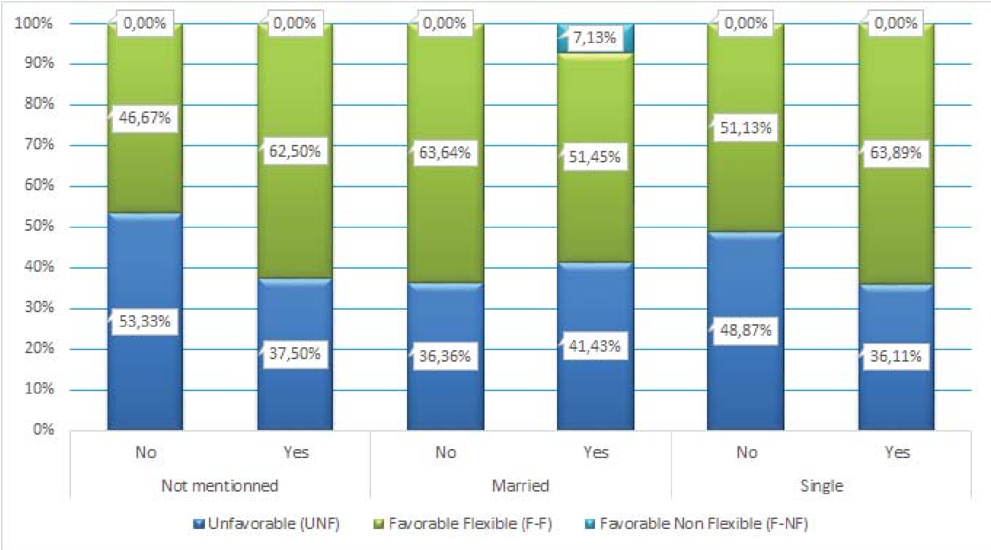

Fig. 7 Neural network results according to marital status and having or not children

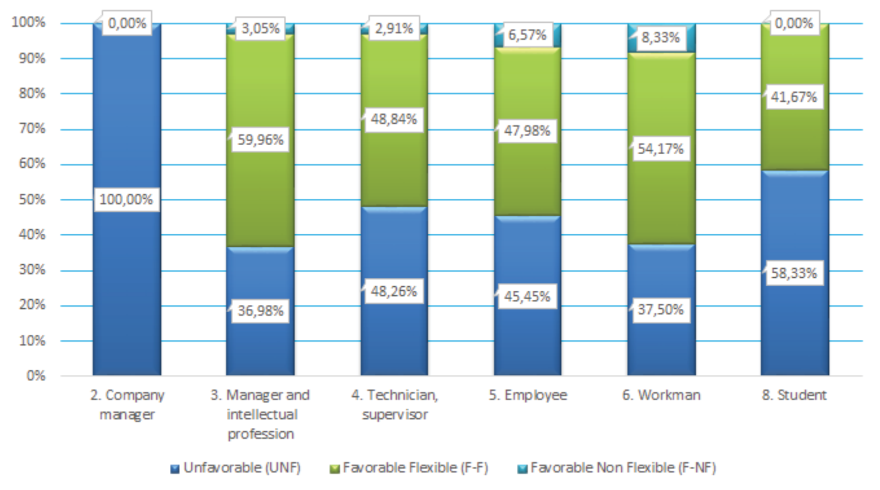

Fig. 8 Neural network results according to the socio-professional categories (INSEE numbering)

Fig. 9 KNN results according to gender

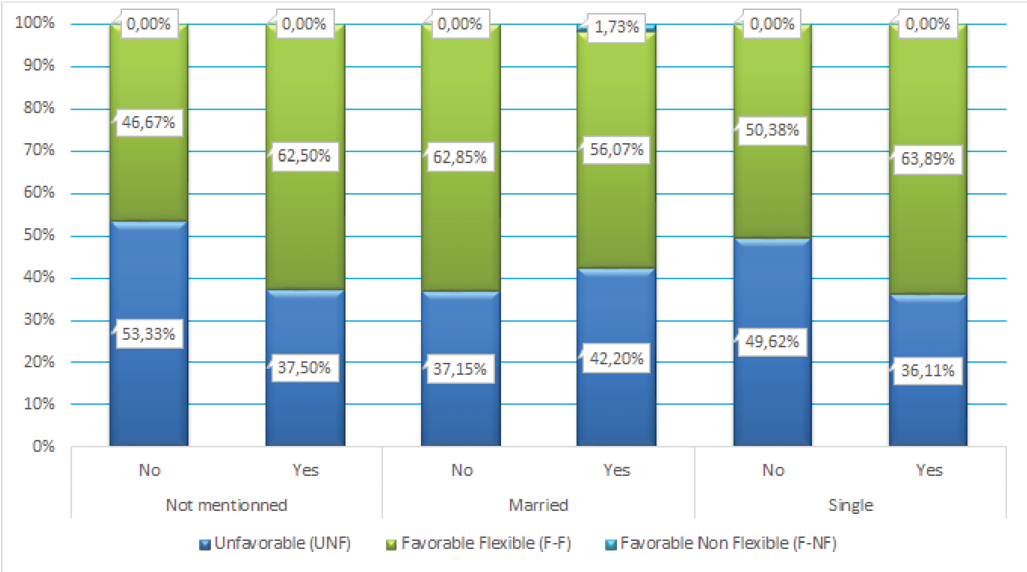

Fig. 10 KNN results according to marital status and having or not children

TABLE II
COMPARISON BETWEEN MLP AND KNN METHODS

	MLP vs KNN similarities (%)
Profiles: *UNF*/ *F-F* /F-NF	98.26% / 96.19% / 24.32%
Gender	94.60%
Socio-professional category	94.60%
Marital status /with children	93.77%

Clearly the results obtained when applying KNN method are very similar to those obtained using MLP neural network method.

3) Impact of the Socio-Professional Category: Fig. 11 depicts the distribution of the persons' profiles according to their socio-professional category.

- In the socio-professional category *"Manager, intellectual professions"*, which is the biggest INSEE category, 340 persons belong to the *F-F* profile, 4 to F-NF profile and 213 are classified as *UNF*. These correspond to $61,94\%$, $0,36\%$ and $37,70\%$, respectively. For this INSEE category, the proportion of *Favorable* people remains greater than those *UNF* with KNN method too.
- The category of *"Employees"* is almost fairly distributed between profiles *F-F* and *UNF* as 98 persons of this category are considered as *F-F* $(51,01\%)$ and 96 persons as *UNF* $(46,97\%)$.

C. Comparison between MLP and KNN Methods

The results obtained with MLP and KNN methods show an accuracy of 97%. Table II summarizes the results similarities obtained with these methods for each profile and also according to the factors considered (gender, socio-professional category, and marital status with/without children).

VI. CONCLUSION

This paper presents a methodology for predicting a population's willingness and flexibility to change the start and the end of its working hours to reduce traffic congestion.

We define three mobility profiles, and considering sociological criteria and constraints related to a person life, we apply a machine learning model to predict the mobility profile of the person. We have compared two machine learning techniques (MLP neural network and K Nearest Neighbor methods) and showed that they lead to very similar results with an accuracy of 97%.

The second part of the paper is dedicated to analyzing the impact of sociological profiles on the results obtained using both techniques. Several conclusions can be reached after analyzing the obtained results.

- Changing the start and the end of the working hours is a solution that most employees can adopt (59% of the surveyed persons are favorable against 41%).
- With the MLP method, 7% of the persons who are favorable are not flexible due to personal or professional constraints, against only 1.75% with the KNN method.
- Gender (male, female) does not affect the preferences for changing the start and the end of working hours.

As future work, we intend to propose temporality scenarios for the persons who are in favor for changing their working hours to reduce congestion.

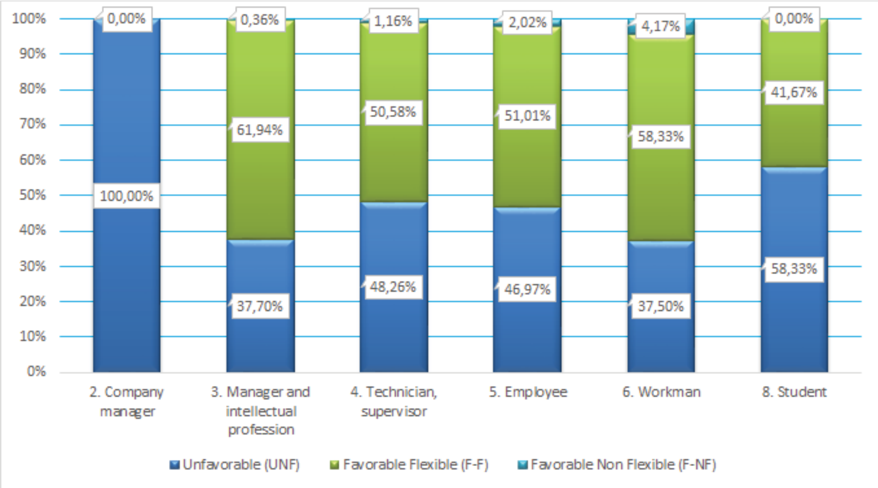

Fig. 11 KNN results according to the socio-professional category

REFERENCES

[1] T. Oguchi, "Redesign of transport systems on highways, streets and avenues," *IATSS Research*, vol. 32, no. 1, pp. 6–13, 2008. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0386111214601953

[2] D. Metz, "Developing policy for urban autonomous vehicles: Impact on congestion," *Urban Science*, vol. 2, no. 2, 2018. [Online]. Available: https://www.mdpi.com/2413-8851/2/2/33

[3] A. Samaha and H. Mostofi, "Predicting the likelihood of using car-sharing in the greater cairo metropolitan area," *Urban Science*, vol. 4, no. 4, 2020. [Online]. Available: https://www.mdpi.com/2413-8851/4/4/61

[4] T. Litman, "Evaluating carsharing benefits," *Transportation Research Record*, vol. 1702, pp. 31–35, 01 2000.

[5] E. Uhlemann, "Introducing connected vehicles [connected vehicles]," *Vehicular Technology Magazine, IEEE*, vol. 10, pp. 23–31, 03 2015.

[6] K. A. Marczuk, H. Soh, C. L. Azevedo, D.-H. Lee, and E. Frazzoli, "Simulation framework for rebalancing of autonomous mobility on demand systems," 2016.

[7] M. Pavone, *Autonomous Mobility-on-Demand Systems for Future Urban Mobility*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015, pp. 399–416. [Online]. Available: https://doi.org/10.1007/978-3-662-45854-9_19

[8] L. J. Basso, C. A. Guevara, A. Gschwender, and M. Fuster, "Congestion pricing, transit subsidies and dedicated bus lanes: Efficient and practical solutions to congestion," *Transport Policy*, vol. 18, no. 5, pp. 676–684, 2011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0967070X1100014X

[9] E. Güresen and G. Kayakutlu, "Definition of artificial neural networks with comparison to other networks," in *WCIT*, 2011.

[10] E. Güreşen and G. Kayakutlu, "Definition of artificial neural networks with comparison to other networks," *Procedia CS*, vol. 3, pp. 426–433, 12 2011.

[11] G. Guo, H. Wang, D. Bell, and Y. Bi, "Knn model-based approach in classification," 08 2004.

Yassamina Berkane is a second-year computer science Ph.D. student at the University of Versailles Saint Quentin, Paris-Saclay in France. She received an engineering degree in electronics from the National Polytechnic School of Algiers and a master's degree in embedded systems and data processing from the University of Paris-Saclay.

Leïla Kloul is an associate professor at the University Paris-Saclay (UVSQ). She has a PhD in computer science from the University of Versailles St-Quentin-en-Yvelines. Her research domains include model based safety analysis and urban mobility systems management.

Yoann Demoli is an assistant professor of Sociology at the University of Versailles Saint-Quentin en Yvelines (UVSQ) and a research associate at the laboratory PRINTEMPS (CNRS). As head of the UVSQ Department of Sociology, his main research interests are social stratification, sociology of spatial mobilities and quantitative methods. He has co-authored Sociology of the Automobile (in French), and has recently devoted his research to the democratisation of air and rail transport.