New approach for a stable multi-criteria ridesharing system

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To my dear parents Mohamed and Amel
For the love they gave me

To my exceptional husband Tarek
For his support and patience

To my loving daughters Yasmine & Nermine
For the happiness they bring to my life
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Abstract

The witnessed boom in mobility results in many problems such as urbanization, costly construction of many highways and air pollution. In an attempt to address these problems, in this master, we are interested in the implementation of a ridesharing system. Ridesharing is recognized as a highly effective means of transport to solve energy consumption, environmental pollution and traffic congestion issues. Indeed, ridesharing can reduce the number of vehicles on the roads to avoid traffic jams and thus it contributes to a reduction in greenhouse gas emissions. Its main thrust resides in sharing transport expenses, meeting different people and making traveling more enjoyable.

In this respect, we introduce in this dissertation an effective ridesharing system, called the Stable Multi-Criteria Rideshare Matching (SMRM) system, that (i) considers users’ personal preferences when sharing a private space with others and (ii) enables a stable matching between driver and passenger sets. The performed experiments show that the introduced system outperforms its competitors in terms of stability quality and cost.

**Keywords:** Smart cities, Social sustainability, Ridesharing , Social preferences , TOP-SIS , Stable marriage.
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Introduction

Since the transport revolution of the twentieth century, the car has rapidly emerged as the main means of transportation in and around large cities. In 2006, nearly 900 million cars roamed the planet. In 2015, the billion was exceeded [1]. Under the shadow of this mobility boom, there are major misdeeds and pejorative impacts affecting the quality of life as well as the biological and environmental balance necessary for the survival of human beings. Indeed, public authorities hope to find solutions to reduce the existing problems and to make transport systems more durable, i.e., economically viable, socially equitable and environmentally sustainable [2].

The focus is on alternatives to individual cars and on the radical change in human behavior. Thus, similar to public transport, walking or cycling, ridesharing has been recognized as a highly effective way of transport to solve energy consumption, environmental pollution and traffic congestion issues [3]. Indeed, it reduces the number of vehicles on the roads in order to avoid traffic jams and thus helps decrease greenhouse gas emissions. Moreover, it allows sharing transportation expenses between several individuals. In addition to the economic and ecological benefits, ridesharing permits, through the grouping of people who know each other or not, restoring a certain communication and to creating and fortifying social bonds. Ridesharing has thus made its entry into the field of research and several systems have been proposed. The purpose of such systems is to enable drivers and passengers to submit respectively their ridesharing offers and requests by specifying their constraints such as their origin, destination and detour tolerance, etc. Once the request is submitted, the system provides a list of pairs (driver, passenger) that satisfies these constraints and maximizes its global objective.

Although there are many attempts to provide ridesharing systems, they are not meeting the expected success, given the lack of motivation of individuals to turn to such systems.

This lack of enthusiasm for this practice is explained in particular by the boredom of traveling with an unknown person. Indeed, sharing a private space as the vehicle is not an interesting idea for many persons, especially if their tastes and habits are different. Passengers and drivers often aspire to have a pleasant ridesharing time and this is not
always the case if they have different social preferences. Everyone has their own personality and their moods. However, classical ridesharing systems mainly focus on the improvement of their potential and performance in ridesharing to fulfill spatio-temporal constraints and to maximize certain objectives. In addition, a rideshare matching solution aiming to maximize the total system objective or the total number of matches may not necessarily maximize the objective of each individual participant. Launched on the path of improvement, we propose in our work to set up an optimized dynamic ridesharing system. Aspiring to the development of a functioning, efficient and competitive system on a large scale, we focused on the notion of satisfaction of personal constraints. Our study was then oriented in this direction and resulted in a new ridesharing system that we call Stable Multi-Criteria Rideshare Matching. The main thrust of our proposal is the selection of matches that promise the satisfaction of drivers and passengers’ social preferences. Furthermore, we consider stability for rideshare matches.

Indeed, the ridesharing problem is treated as a matching problem where drivers are assigned to passengers. Our objective is to create a perfect matching of drivers and passengers such that there does not exists any pair of a driver and a passenger who prefers each other to their current partners. This notion of stability is similar to that of the stable marriage problem. To achieve this, we rely on the multi-criteria decision-making method (MCDM), which is considered one of the most important branches of operational research and decision theory.

This report is divided into four chapters: the first introduces the ridesharing that is recognized as a highly effective means of transport to solve energy consumption, environmental pollution and traffic congestion issues. In the second chapter, we highlight a state of the art of existing rideshare systems with a focus on their limitations and gaps and we summarize the methodological tools underlying our approach. In the third chapter, we present the architecture of our system by detailing its main components. The methodological concepts and algorithms leading to such modeling are also described in this chapter. Evaluation and experimentation will be the subject of the forth chapter. The latter emphasizes the realization of the approach, the choice of the evaluation metrics and the experimental environment.
Chapter I

Ridesharing: An alternative, ecological and economical means of transport

1 Introduction

With the lengthening of distances and travel times, causing an explosion of mobility that is not without harmful consequences, the private car has become a source of trouble after the dazzling success of which it was crowned. Indeed, in addition to noise pollution, the pressure it exerts on individuals and huge expenses, the massive use of the personal car causes the extermination of the own ecological concept. Meeting the challenge of reducing the excessive use of the private car is all the more difficult as it exerts an immeasurable pressure on individuals creating strong links of dependence. One solution lies in the reasonable non-abusive use of the private car. Group access, which in addition makes use of private cars, helps to considerably reduce the number of moving cars. This concept is the definition of ridesharing.

2 Motivation: Effects of the car on society

The European Union has a fairly dense transport network, including road, rail, metropoli-tan, maritime, etc. The use of personal vehicles is popular, indeed, 80% of urban travel is done with this means of transport [4]. The environmental impact and congestion of the road network have become a major concern for the authorities, who are trying to reduce or to see better use of this means of transport.
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2.1 Private car: Access and convenience

The road transport has been one of the most important means of transport and has been indispensable to the development of commerce and industry. All the movement of people, freight and information has begun and ultimately has ended by making use of roads. These movements have always been fundamental components of the economic and social life of societies.

Contemporary economic processes have been accompanied by a significant increase in mobility and higher number of individual cars. Although this trend can be traced back to the industrial revolution, it significantly accelerated in the second half of the twentieth century and the demand of individual car has rapidly increased as the main means of transportation in and around large cities.

The statistic in Fig. I.1 represents the number of cars sold worldwide from 1990 through 2018. 81.6 million automobiles are expected to be sold by the end 2018. This figure equals double of all ten-year car sales from 1990 to 2000.

![Figure I.1 – Number of cars sold worldwide from 1990 to 2018 (in million units)](https://www.statista.com/statistics/200002/international-car-sales-since-1990/)

Indeed, due to its many advantages: its performance in terms of speed, handling, comfort, safety and reliability and the great adaptability it represents (short or long distance travel, urban, peri-urban or extra-urban area ...); the individual car has become a necessity in people’s lives. Therefore, joining convenience to ease of access and spatio-temporal flexibility, individuals are increasingly moving towards this mode of transportation. The latter has become, over time, necessary for their psychological balance and peace of mind.

Despite its decisive benefits, even changing the behavior and lifestyles of individuals, the private car prevents the prospects of advanced and sustainable mobility to...
2 Motivation: Effects of the car on society

go to good advantage. It is therefore behind many obstacles that run counter to the implementation of a clean and sustainable development process.

2.2 Disadvantages of the private car use

The car threatens the centrality of the urban organization. Also, it affects the relationships between people because it destroys urban sociability thus generating economic distortions.

2.2.1 Environmental impact

To move, the car needs gasoline, diesel or natural gas, etc. It contains a battery, lubricating oil, and a catalyst composed of precious-metal such as platinum and rhodium. These few examples are enough to understand how difficult it is to measure the environmental impact of a car. Road transportation is linked with a wide range of environmental considerations. The nature of these environmental impacts is related to the infrastructures over which they operate, their energy supply systems and their emissions. While consuming large quantities of energy vehicles also emits numerous pollutants such as carbon dioxide and nitrogen oxide which damages many ecological systems. The structure of final energy consumption in the European Union in 2015 by sector shows that road transport with 30% accounted for the biggest share of energy consumption (Fig. I.2). A breakdown by sector presented in Fig. I.3 is tangible evidence of this, based on figures extracted on CO2

Figure I.2 – Final energy consumption by sector, EU-28, 1990-2015

2. Source: Energy, transport and environment indicators, 2015 Edition.
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emissions from different modes of transport. Statistics at the origin of these histograms reveal that road transport in the European Union remains the most polluting mode with 94% of the CO2 emissions.

![Figure I.3 – EU-28 GHG emissions by mode of transport in 2015](http://www.who.int/violence_injury_prevention/road_traffic/en/)

2.2.2 Safety issues

The large number of cars on the road generates negative impacts not only on the environment but also on the fluidity of the traffic thus creating traffic jams and a congestion which can be at the origin of accidents or any other type of incident. Indeed, according to data from the World Health Organisation[^3^], over three thousand people die every day on the world’s roads and tens of millions of people are disabled or injured every year. In parallel, public transport helps to make road transport more fluid by transporting large numbers of people on specific routes, thus reducing the number of cars on the roads. Indeed, for 60 people transported by bus, the occupied surface does not exceed that intended to support two cars. While a car only carries an average of 1.5 passengers [^7^]. In addition, reserved lanes intended for transport far from road traffic considerably help to smooth traffic and thus reduce accidents.

2.2.3 Societal issues

Since the 1970s, the proliferation of ring roads, highways and suburban road networks have encouraged many city dwellers to leave city centers with rents whose prices are too high, to join the suburban housing estates. The car contributes to the dissolution of the limits of the city (peri-urbanization) and it is the birth of “rurbains”, who depend on the...
car to go to work or do their shopping.
Thus the emergence of this automobile civilization has caused a brutal transformation of the classical city towards a city where the car progresses irresistibly thus causing an increasing separation of the zones of activity of the zones of habitat which increases the distance to be traveled and the road traffic.

Various societal effects remain after the growth of car traffic: noise, stress, pollution, lack of space for pedestrians, etc. All of these negative effects contribute to the dispersal and remoteness of habitat, businesses, services, workplaces and leisure facilities that in turn cause increased travel needs and increased car traffic. This is a vicious circle, the phenomenon of which is further reinforced by the fact that the dispersion and distance of the various functions leads to a reduction in accessibility for non-motorized users and for those in common.

2.3 Towards sustainable mobility

Public authorities hope to find solutions to reduce existing problems and encourage innovative initiatives that aim to make transport systems more durable, i.e., economically viable, socially equitable and environmentally sustainable [2].

There are several innovative projects to develop decision support software platforms that offer cost-effective and flexible solutions. These platforms therefore offer sustainable mobility development solutions in the sense that they propose easy solutions with the required knowledge. The latter are, for example, real-time information on traffic conditions, measurements of harmful gas emissions, and so on. Also in the context of innovative advanced mobility projects, some organizations offer to help travelers in their travels based on calculations of travel times for example. Their impact in this context may concern more efficient management of travel, control of the environmental impact, an incentive for the use of public transport or even the minimization of costs, etc.

Efforts in this direction have shifted towards green technologies and clean modes of transport while trying to remain in the cozy environment of on-demand transport services or the personal cars. The aim is to reduce the number of cars on the road, thereby reducing its negative impact on traffic flow and the environment while maintaining its flexibility. A key solution lies in the concept of a shared car that heals the image of the particular automobile, dislodging it from the prevailing context of which it has always appeared while preserving the advantages it presents. Researchers and industrialists have collaborated to immerse innovation projects in this context and put into practice the ideas expressed by these projects, thus combining pragmatism with theoretical ideologies. In doing so,
many practices are born and systems offering more or less advanced services compete with originality and performance. 
Transport problems, which are now partially solved, remain far-reaching. Advanced mobility is thus placed at a probative stage in the fields of industry as well as research. In our work, we address the problem of the shared car and more specifically the concept of ridesharing.

3 Ridesharing

With ridesharing, the private car gave birth to a means of transport that was in nature individual but became collective. Several ridesharing systems have been emerged as a result of the development of several works to improve the quality of life, in particular by considering the development of the transport field in an improving context.

3.1 A mode with high potential

Ridesharing has been recognized as a highly effective way of transport to solve energy consumption, environmental pollution and traffic congestion issues [3]. Indeed, it reduces the number of vehicles on the roads in order to avoid traffic jams and thus helps decrease greenhouse gas emissions. Moreover, it allows sharing transportation expenses between several individuals. In addition to the economic and ecological benefits, ridesharing permits, through the grouping of people who know each other or not, restoring a certain communication and to creating and fortifying social bonds.

3.2 Principle and definitions

Ridesharing refers to the shared use of a vehicle by a non-professional driver and one or more passengers for the purpose of performing all or part of a common travel [8]. Ridesharing is then the matching of travelers doing all or part of a trip they would otherwise have done alone.

To better present the concept of ridesharing, we present some definitions:

**Passengers:** At the base, they are pedestrians looking for a possible rideshare offer that can bring them to a specific place, these people may or may not own their private cars. They are thus defined as service providers initiating requests to be driven between two given points in the context of a desired trip.
3 Ridesharing

Request: A rideshare trip can only be done if a request exists. This is a request from a passenger who wishes to travel by car from one place to another. A request relates to a specific travel requirement according to which the passenger determines the date and time of travel, where he wants to go, etc.

Drivers: This refers to the driver of a car in the context of ridesharing with one or more other passengers. These users of the service use in the general case their own vehicle. In addition, the driver has his own travel needs which he defines through the submission of a ridesharing offer.

Offer: It refers to the driver’s travel parameters (usually the owner of the car used for ridesharing). These parameters define the specificities of the trip to be traveled: origin, destination, date, departure time, number of places available, etc.

3.3 Ridesharing problem classification

According to the procedure for using the ridesharing service, we split ridesharing problem into two different types: Long-term RideSharing Problem (LTRSP) and Daily RideSharing Problem (DRSP).

In the LTRSP, each user has to act as both a driver and a passenger and a solution is to define rideshares where each user will in turn, on different days, pick up the remaining rideshare members. The objective is to minimize the amount of vehicles used and the total distance traveled by all users, subject to car capacity and time window constraints. The LTRSP can be considered as a combination of a clustering problem and a routing problem. It requires finding the rideshare members relatively close to each other and identifying the route and schedule for each member in the rideshare. Fig.4 presents an example of LTRSP. On the contrary, in the DRSP, a number of users declare their availability for picking up or bringing back other users on one particular day. Hence, these users are considered as drivers, and the other users being picked up or bringing back are considered as passengers. Then the problem becomes to assign passengers to drivers and to identify the routes to be driven by the drivers. Since in the DRSP, the drivers and the passengers are known in advance, the objective is to construct path starting from each driver and going through as many passengers as possible with respect to the car capacity and time window constraints, and to minimize the total travel cost.

The DRSP model is based on daily schedule, so the participants change every day. It is a model normally used by the commercial website which organizes daily rideshare service.
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Figure I.4 – An Example of the LTRSP

among different members. Figure I.5 shows an example of the DRSP. The LTRSP is a more

Figure I.5 – An Example of the DRSP

stable ridesharing model; the users in LTRSP will not change frequently in a relatively long period of time. This model is usually used by large companies, organizations and universities which provide long-term rideshare service for their employees or students. In the academic point of view, solving the DRSP can simply be done by clustering users into rideshares based on a long-term schedule, and each rideshare member has to act as a
driver on a different day. On the other hand, we believe that the DRSP is a more valuable topic for research, since it has its own characteristics and its optimization challenges. Therefore, the DRSP is chosen to be the focused ridesharing.

4 Ridesharing system

4.1 System principle

The ridesharing system connects drivers and passengers wishing to share a trip and the associated costs. Drivers publish their available seats and passengers buy them online, on trips like home-work. It enables drivers and passengers to submit respectively their ridesharing offers and requests by specifying their constraints such as their origin, destination and detour tolerance etc. Once the request is submitted, it provides automatic ride-matching between participants. This rideshare system may use technology such as Global Positioning Software (GPS), continuous internet connection and smart phone software to remove the requirement to pre-arrange trip schedules well in advance as matches are made based on current proximity. Payment can be made in cash in the car or also through PayPal on the ridesharing’s mobile phone application. Registration is typically on a handset with fewer requirements for details as the current location will already be known through the phone’s GPS function. This system can also include a post-ride rating for the driver or passenger which would be available to other program users to help them decide whether they want to share a ride with that person.

4.2 Matching constraints

Ridesharing does not make sense and has no place to be unless certain conditions are fulfilled. Classical ridesharing systems mainly rely on the matching of spatio-temporal constraints between a driver offer and a passenger request. These constraints essentially refer to the correspondence between offer and demand, thus making it possible to verify:

— Timing of trips offered and required; it is probably the most important consideration since time tends to be a most constraining factor. Both riders and drivers must provide information on their time schedule preferences. These must come nearer, or even better, confused.

— Coincidences between trips; the passenger trip fits within to the driver itinerary. This does not exclude the fact that a small detour is tolerated to pick up or to drop
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off one or more passengers, depending on the motivation of the driver and the other passenger.

4.3 Kinds of ridesharing systems

There are several distinct forms of ridesharing systems, they each address different trip needs and have different characteristics.

Commuter
Commuter ridesharing system caters for individuals and organizations looking for regular rideshare matches for work or other regular trips. These are the typical commercial rideshares that provide free membership for individuals who register but if an organization wishes to create a closed network available only to their employees or students it will typically be required to pay a fee for the service.

Long distance / once off
Long distance ridesharing system provides matches for people travelling long distances, typically as once-off trips. This mode is targeted towards travelers who have planned schedules well in advance but who may have some flexibility in terms of departure timings. As a form of pre-organized hitchhiking, this rideshare system typically has less registration and security requirements than commuter ridesharing as the users only utilize the service occasionally. Travel to events and festivals would also be considered part of this category.

Casual/ flexible
Casual ridesharing system, also described as 'slugging' system, is rideshare network that operates without pre-organization and contact. This rideshare system involves drivers and passengers simply turning up to the same departure location and matches are made on-the-spot for trips to a similar destination. It has typically developed as a means to use high-occupancy vehicle (HOV) lanes or to share toll payments. This ridesharing system is not supported by public or employer organizations. Advantage of this ridesharing is the reduced commitment for participants; if they don’t turn up on the day they won’t be letting anyone down. The associated disadvantages are a lack of security and reduced ability to be replicated in other locations as this ridesharing arises organically to address a specific need in locations with a large number of participants making similar trips.

Dynamic
Also known as real-time ridesharing system, it provides automatic ride-matching between
participants at short notice or while the driver is already travelling. This rideshare system uses technology such as Global Positioning Software (GPS), continuous internet connection and smart phone software to remove the requirement to pre-arrange trip schedules well in advance as matches are made based on current proximity. Because of the spontaneous nature of this system, the latter will typically suggest a cost per kilometer or a ridesharing fare. Payment can be made in cash in the car or also through PayPal on the ridesharing’s mobile phone application. Registration is typically on a handset with fewer requirements for details as the current location will already be known through the phone’s GPS function. This system can also include a post-ride rating for the driver or passenger which would be available to other program users to help them decide whether they want to share a ride with that person.

Being interested in the issue of dynamic ridesharing, we focus essentially on this concept and we propose an optimized approach for ridesharing system.

5 Conclusion

In this chapter we discussed how ridesharing systems contribute to improve the environmental conditions in which people evolve. The concept of ridesharing has many advantages, including reducing the number of cars in circulation per kilometer. Indeed, the personal car has become, due to this concept, a means of collective travel accessible to the general public. It is within this context that we directed our work to propose an innovative approach whose foundations were built on the basis of a study of the principles and concepts lacking the systems erected by the development of this phenomenon. A thorough study of the history of ridesharing as well as a description of the methodological tools used in our proposed approach will be highlighted in the next chapter.
Chapter II

Related work

1 Introduction

In recent years, ridesharing has become a very popular research topic for the industry and the researchers. In this chapter, we first summarize the pioneering approaches of ridesharing and we define our main motivations justifying the great interest that we carry to it. In section 3 and section 4 we present an overview of the methodological tools that form the basis of our approach, which are Multi-Criteria Decision-Making and stable matching.

2 Survey on ridesharing

2.1 Industrial work on ridesharing

2.1.1 Static ridesharing

Numerous Internet sites allow the proposition and the demand of rideshares, whether regular or occasional, of proximity or long distance. In the latter case, some sites offer online search engines for ridesharing, which calculates the routes and the best possibilities for the driver and the passenger. These rideshare bulletin board services are often free and easy to use. In Tunisia, ridesharing is not yet well recognized. Only a few static internet sites are being hosted like tawsila.tn and partagi.tn. In France, after the launch of BlaBlaCar in 2006, ridesharing is booming. By 2010 this site had more than 600,000 registered members and was attracting more than 10 million page views.

1. https://www.tawsila.tn/
2. https://www.partagi.tn
3. https://www.blablacar.fr/
2 Survey on ridesharing

per month. BlaBlaCar has since expanded significantly, with 25 million users across 22 countries [9].

In 2014, SNCF just played a double blow by opening a new ridesharing platform called IDvroom⁴. It is an open portal; i.e., it is not reserved for SNCF customers. The goal was to attract new revenue and not be overtaken by the already ubiquitous BlaBlaCar. In addition, this project is part of its "door-to-door" travel strategy, which began with personal services such as car rental on arrival of the train, chauffeur service that takes passengers or bring back from the station or take charge of luggage at home. The principle of iDVROOM is about the same as that of its competitor. The user has the choice between a single trip and regular commute. The driver fixes to passengers the cost per kilometer. Passengers can pay the amount of their trip directly online. On arrival, they send the driver their passenger code sent by the site when booking. Afterwards, the money is transferred to the iDVROOM wallet, which will then pay the driver after pocketing a commission [10]. Static systems require booking in advance based on static reasoning, ignoring instant events. Thus, these systems do not allow a real-time allocation of vehicles, which does not provide an instant response to the user. In order to cope with this deficit, dynamic ridesharing systems are developed with real-time management of the service. This type of ridesharing has a strong potential for development due to its main principles: real time, optimization of trips and the guarantee of a reliable service.

2.1.2 Dynamic ridesharing

Dynamic ridesharing consists of providing users in real time with an opportunity to rideshare at short notice. Conversely to static ridesharing, it allows more flexibility, credibility and less interdependence between participants. The principle is based on an instantaneous exchange of data, between drivers and potential passengers, via at least a Smartphone equipped with a GPS tool, allowing real-time geolocation of passengers and drivers, and allowing them to be connected. With a sufficient number of members, the operation is flexible and offers a good quality of service: the probability of finding the right correspondent is considerable. In recent years, dynamic rideshare experiments are emerging. Among the systems made, we can mention:

— Piggyback⁵ developed by a French research team. Via Piggyback, the driver can enter his destination. If passengers are interested, they send a request, via mobile phone equipped with GPS, which can be accepted or not. After each rideshare trip,

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4. https://www.idvroom.com/
5. http://www.piggybackmobile.com/
the driver has the opportunity to report the passengers transported as favorites or not. Users have the option to cancel their queries, but if they wait until the last moment penalties can be applied. These penalties can be financial or in terms of "rating".

— GreenMonkeys, supported by the Clem' company, it offers ridesharing services for businesses. Drivers and passengers specify the origin and destination of their trips on the platform, and Greenmonkeys guarantees that transport will be available to make the trip. If the rideshare solution is impossible, the company agrees to pay the taxi. The payment of the trip is done automatically by an electronic wallet system.

— Carma Carpooling, set up by the transportation technology company Carma, available from an Iphone equipped with GPS. It allows for dynamic carpooling. Carma is also developing solutions for shuttle services and Transportation On Demand. The driver enters his destination and the empty seats are offered to potential passengers. If a passenger wants a trip at a certain time, the system selects the most suitable driver and offers the driver the detour to make. If the driver accepts, a voice can guide the driver to the appropriate stop where driver and passenger can meet. On the Iphone, the driver can evaluate between 1 and 5 his experience with the passenger in question. Carma automatically manages the sharing of fees between carpoolers.

Nevertheless, despite technological advances and efforts in this domain, most of the existing systems implementing a real-time ridesharing service have remained at an embryonic stage due mainly to lack of security and the automation gap. In addition, compared to static systems, the platforms dedicated to dynamic ridesharing have the advantage of consulting in real time the list of offers of vehicles in circulation. On the other hand, the optimization aspect is completely ignored. Indeed, these systems do not integrate optimization algorithms to generate Driver / Passenger matching.

2.2 Literature review on ridesharing

With regard to the dynamic rideshare systems, we can say that they have three components. A rideshare system is composed of 1) an algorithm that matches the participants with each other, 2) according to their constraints, 3) to finally optimize a certain objective.

In the following, we outline how these three notions have been treated in the literature.

6. http://clem.mobi/covoiturage
7. https://www.gocarma.com/
2 Survey on ridesharing

2.2.1 Matching algorithms

There are several types of matchmaking algorithms for ridesharing. A state of the art has been realized by Agatz et al. [11]. According to the latters, dynamic rideshare systems can be classified according to the number of drivers and passengers considered. Systems that allow the driver to take a single passenger differ from systems that can take more than one on the same trip. On the passenger side, the systems are classified according to whether the passenger can only ride with one driver during his trip, or can connect portions of the trip with different drivers. According to Agatz et al., we can classify ridesharing systems into four categories: Single Driver - Single Passenger, Single Driver - Multiple Passengers, Multiple Drivers - Single Passenger and Multiple Drivers - Multiple Passengers.

Table II.1 summarizes for each variant the problem associated with it.

|                         | Single Passenger                      | Multiple Passengers                      |
|-------------------------|---------------------------------------|-----------------------------------------|
| Single Driver           | Matching of pairs of drivers and passengers | Routing of drivers to pick up and drop off passengers |
| Multiple Drivers        | Routing of passengers to transfer between drivers | Routing of drivers and passengers |

Table II.1 – Ridesharing variants

**Single Driver - Single Passenger Systems**

These are the simplest and are the basis of the rideshare study. Research on this subject aim to match a passenger and a driver while fulfilling certain constraints. In this case, we find ourselves in the context of matching problems, that is to say that we have agents (drivers) who must be matched to tasks (passengers) the costs of each match (detours for example). A survey of the most useful of the variations of the matching problem was presented in [12].

**Single Driver - Multiple Passengers Systems**

By adding a capacity to the vehicles used, we fall into this variant. This adds a dimension to the problem and we go completely out of the conventional matching problem, since the constraints of the passengers are multiple and different. In this class of problems, there are systems for picking up employees to go to the workplace. Baldacci et al. [13] offer a method to respond to a company that wants its employees to come to work and return home with as few vehicles as possible, i.e. by ridesharing. The method must therefore
determine the vehicles to be used and the paths that must be traveled to pick up all employees. This is what is commonly referred to as "dial-a-ride" problems and can be found in the literature review presented by Cordeau et al. [14]. Clearly, a problem "dial-a-ride" is to find the routes and times of pick up and drop off of n users by m vehicles knowing the origins and destinations of n users while minimizing the costs of travel and respecting a set of constraints, such as user preferences. The main difference between this type of problem and the rideshare problems is that in ridesharing, drivers do not come from one or more sources and are independent entities, not attached to a company or service [11].

Multiple Drivers - Single Passenger

It is a question of finding a sequence of drivers that would bring the passenger to destination. In practice, however, it is difficult to take three or more different cars in succession to make a single trip, except perhaps for very long trips. It is for this reason that this category of problem is much less studied than the preceding categories. Drews et al. [15] were interested in the subject and proposed a "multi-hop" ridesharing method, that is to say, with vehicle changes, based on network modeling and graphical timetables. Similarly, using a graph whose network is only composed of drivers’ geographic and temporal offers, Herbawi et al. [16] stated a method where passengers had to find an acceptable path to go from their origin to their destination on this graph.

2.2.2 Constraints of rideshare matching

Spatio-temporal constraints

Classical ridesharing systems mainly rely on the matching of spatio-temporal constraints between a driver supply and a passenger request. Indeed, the travel date and time of both the passenger and the driver should be closely matched. In addition, it is mandatory that the passenger trip fits within to the driver itinerary. This does not exclude the fact that a small detour is tolerated to pick up or to drop off one or more passengers, depending on the motivation of the driver and the other passengers.

Wen et al. [17] presented an approach that mined regular routes from the historical GPS trajectories of a user for ridesharing recommendations. In this work, only the origin and destination regions as well as the time property of each travel were taken into account to match driver /passenger candidates. In this respect, an optimization model based on mixed continuous-integer linear programming was proposed in [18] to maximize the performance of dynamic ridesharing systems. This approach looked for the best path in the
considered transportation network to minimize the difference between the desired departure and arrival times.

It is worth mentioning that other approaches have been interested in checking the tolerance in detour constraints for drivers. For instance, a routing optimization model for ridesharing a taxi was suggested in [19]. The objective of the proposed model was to minimize the travel cost and to maximize the passenger satisfaction. The latter was defined by the direct travel time, the extra riding time caused by ridesharing and the waiting time. Additionally, in [20] a matching algorithm for dynamic ridesharing based on network partitioning was presented. A route was expressed as a sequence of tiles which was referred to as a corridor. Only passengers, whose origin and destination were inside the corridor of an existing trip, were matched in possible ridesharing. To be matched, the additional time set by both the driver and the passenger associated to ridesharing had to be below a specific limit. Moreover, the approach in [21] dynamically matched trip requests to vehicles while satisfying two constraints: a waiting time defining the maximal time allowed between making the request and receiving the service and a service constraint, defining the acceptable extra detour time from the shortest possible trip duration. Interestingly enough, Schreieck et al. [22] put forward a matching algorithm for ride requests and offers that would check whether a driver could ride with a passenger without violating the maximum detour constraint they had set. In the same vein, Cici et al. [23] took as an input some information about the desired trajectories and spatio-temporal constraints of drivers and passengers and returned a matching that not only met individual user constraints but also maximized the total revenue for the system. A match would be feasible as far as the driver’s tolerance in detour and the passenger’s timeline were fulfilled.

On the other hand, an approach that took into account both the maximal price the passenger was willing to pay for the service and the maximal waiting time before being picked up was defined in SHAREK [24]. Among the set of drivers that could provide such a service, SHAREK reported only the skyline element, i.e. maximal vector of these drivers according to the price and the waiting time.

**Personal preferences**

The aforementioned systems mainly focused on the improvement of the potential and performance of ridesharing to satisfy spatio-temporal constraints. However, a few approaches in literature have paid attention to social constraints to provide an optimal matching that would satisfy users’ preferences. In this respect, the iCAP system [25] proposed a probabilistic method that provided an optimal matching of drivers and passengers’ preferences. The system considered several parameters related to personal profiles such as smoking, gender,
Related work

social behavior, as well as service related parameters like punctuality and itinerary cost, which increase the degree of reliability of the decisions reached. Despite the high-level and formal description of the iCAP functionality, the approach lacked detailed descriptions on the matching algorithm to find the best passenger.

Furthermore, a topic based publish-Subscribe model, where the publisher was the vehicle rider and the subscriber stood for the ride seeker, was introduced in [26]. The system provided gender, smoking, age and marital status as preference options to riders and ride seekers. Rider and ride seekers had the freedom of choosing the importance of each preference, i.e. the preference level. The system would match users according to their preferences, but this did not imply a correspondence between the preference and the actual profile of the partner. In addition, no experimental evaluation of this approach was provided.

Moreover, the ride-sharing problem was formulated in [27] as a multi source-destination path planning problem, where each driver could generate sub-optimal paths according to their own requirements by suitably adjusting the weights of some factors such as time, occupancy, social strength or closeness. In this approach, a social closeness model was proposed, which incorporated the personalized preferences and used current social interests to bring the most similar people closer, raising the chance of matching. Feedback and reliability scores in the form of reputation were also incorporated in the model.

In the same breath, the stable roommates problem was adapted for the matching problem of one-on-one passengers (non-vehicle owners) [28]. A matching model was performed based on ridesharing preferences, which included personal preferences and travel cost savings. The factors of user preferences were personality and steadiness of user personality. Added to that, a web-based software tool for the management of a carpooling service called PoliUniPool was developed in [29]. The system allowed some social network functionalities; e.g., drivers were able to create "pre-arranged crews", and users might specify individuals they preferred or disliked.

Other systems have been linked with social networks like the SRSS system described by [30]. The latter assumed the existence of a social network data source in which users were connected by means of groups and interests and used the "strength of social connection" to prioritize matches. Mobile phones with positioning technologies were utilized for tracking and communication.

Besides, an auction model was developed in [31] to tradeoff the minimization of vehicle kilometers travelled, i.e. greenhouse emissions, with the overall probability of successful rideshares. This model permitted users to set some preferences such as user ratings and social network status other than the travel distance and time.
With regard to the optimization objectives targeted by ridesharing systems, most aim to reduce the total distance traveled or more precisely the total trip time. On the other hand, some researchers are proposing alternative methods. Kleiner et al. [31] proposed a system based on auctions. Depending on the detour to be made, users set prices and drivers choose knowingly their match based on the price offered and detour to achieve. In this way, ridesharing alternatives were naturally regulated according to supply and demand. Another category of objectives is to perform a multi-objective optimization. This is to simultaneously optimize a list of objectives. In this case, not all objectives are optimal at the same time. Nevertheless, the idea is to be in a position where all the values of the objectives are at the so-called Pareto optimality [32]; this means that at this point, any attempt to improve one objective will automatically lead to the deterioration of another objective. For example, Herbawi et al. [16] proposed a ridesharing system whose three objectives to be minimized are the cost and the duration of the trip as well as the number of vehicles taken by a passenger to complete the trip.

On the other hand, systems that fulfill social preferences, had incorporated preferences into a single objective function, called the weighted sum function. The optimization problem has been reduced to the optimization of this function. However, the weakness of this model stands in the process of summarizing the different criteria. Through combining various dimensions, and consequently multiple units, the weighted sum model assumption has been violated and the result has been equivalent to "adding apples and oranges" [33]. Since the satisfaction of user preferences has to deal with multi-constraints with different units, the weighted sum model cannot be used without major changes in its strategy. In our approach, we apply a Multi-Criteria Decision Making (MCDM) method to tackle this issue. To introduce the concept, a thorough study of the decision support process and its products in the case of multi-criteria decision support will be presented in the next section.

To better optimize our system, we aim afterwards to maximize the objective of each individual participant. Our objective is to create a stable matching of drivers and passengers such that there does not exist any pair of a driver and a passenger who prefers each other to their current partners. This notion of stability is analogous to that defined in the well-known stable marriage problem, which will be highlighted in the last section of this chapter.
3 Multi-Criteria Decision Making

In this section, we will focus on the first methodological tool that will be used in our approach for the optimization of a ridesharing system. In order to build a multi-criteria evaluation model, we rely on Multi-Criteria Decision Making (MCDM) method which is considered one of the most important branches of operational research and decision theory [34].

3.1 Decision support

It is common in a decision support study to have to take into account several points of view to compare the relative attractiveness of the various actions likely to solve the problem of decision considered. Decision support uses techniques and methodologies from the field of applied mathematics such as optimization, statistics, and decision theory as well as less formal domain theories such as organizational analysis and cognitive science [35].

Roy et al. [36] define decision support as: "The activity of the person who, based on models clearly explained but not necessarily completely formalized, helps to obtain elements of answer to the questions posed by a decision maker, elements that help to inform the decision and normally to prescribe a behavior likely to increase the coherence between the evolution of the process on the one hand, the objectives and the value system in the service of which this decision maker is placed on the other hand."

Thus defined, decision support is only part of the search for a truth. Theories or, more simply, the methodologies, the concepts, the models, the techniques on which it is based, have, most often, a different ambition: to reason the change that prepares a decision-making process in order to increase its coherence with the objectives and the value system of the actor for whom or on whose behalf the decision-making aid is exercised [37].

Indeed, Martel [38] supports the fact that a decision-making activity "implies a minimum of insertion in the decision-making process: it is done essentially with the decision makers in the establishment of a real relation of help". For Roy et al. [36], a decision issue is not an object that preexists; The wording given to it cannot, in general, be totally objective and cannot be considered independently of the relationship between the individual and reality.

In this sense, Landry [38] notes that the success of a decision-making process in an organization requires an understanding of the entire decision-making process in which this support is embedded, which implies an ability to adequately grasp the problem that just-
3 Multi-Criteria Decision Making

tifies the origin and supplies this process later.

3.2 Multi-criteria decision analysis

In a decision-making process, when constructing the evaluation model, it is rare to lead to only one criterion corresponding to a single point of view on which the decision-maker expresses his preferences \[39\] \[40\] \[41\]. It is therefore necessary to consider several points of view (costs, human resources, safety, environment, etc.) in the subsequent construction of the evaluation model \[42\]. The decision in the presence of multiple criteria is difficult because the criteria are often conflicting. Multi-criteria decision support was then developed to offer both an approach and tools of solutions to complex decision-making problems \[43\]. Multi-criteria analysis is now considered one of the most important branches of operations research and decision theory \[44\] \[45\].

Technically, multi-criteria decision support is developed to deal with several classes of decision problems (choice, sorting, description, ranking ...) while considering several criteria, often conflicting and not commensurable, while seeking to best model the preferences and the values of the decision maker \[46\] \[34\]. Also, Vincke \[47\] defines multi-criteria decision support as: "Multi-criteria decision support is intended, as the name implies, to provide a decision-maker with tools to progress in resolving the decision-making problem, where several, often contradictory, points of view must be taken into account."

3.3 MCDM in ridesharing systems

Although MCDM methodology has gained more and more appreciation and popularity among transportation researchers, few studies proposed a multi-criteria approach to investigate the optimization problems related to ridesharing system \[48\]. Worthy of mention, the work of Filcek et al. \[49\] where a model of the joint problem of matching carpoolers and routes planning as a multiple criteria optimization problem was proposed. The AHP method is used to collect preferences of the carpoolers and involve it to compute aggregated cost function for common routes of the driver and passengers assigned to him, to obtain finally the best routes presented to drivers. A Multi-criteria Decision Support System MDSS is proposed in \[50\] in order to create an intelligent tool for carpooling. In the context of strategic decision making, AHP and ELECTRE methods are integrated to solve the problem that optimizes the total revenue of drivers based on the car’s capability and the time schedule. Li et al. \[51\] employ a method combining AHP and GIS with big data to determine the optimal locations of future stations. The AHP method is used to determine the weights of the decision criteria which are potential users, potential
travel demand, potential travel purposes and distances from existing stations. Moreover Awasthi and Chauhan [52] present a hybrid approach for evaluating environment-friendly transport solutions. AHP method is used to structure and rate the measures for transport sustainability evaluation. All the above mentioned approaches have used the AHP method. The TOPSIS method is also known as one of the most popular methods among MCDM methods. In our approach, we propose to apply it to rank possible matches for each user according to his social preferences. These preference lists are then used to compute the stable matching.

4 Stable marriage

The ridesharing problem is treated as a matching problem where drivers are assigned to passengers. To address this problem, we proposed a strategy based on the Stable Marriage Problem SMP. So it is important to describe this theorem before presenting our approach.

4.1 History

The analysis of correspondence mechanisms is based on an abstract idea: If rational individuals, who know their interests and behave accordingly, simply engage in unrestricted mutual exchanges, then the result should be effective. If this is not the case, some people are developing new exchanges that would be more favorable to them. A correspondence where the individuals concerned perceive no interest or gain in making further exchanges is called "stable" [53] [54]. The notion of stability is a central concept in cooperative game theory that is considered an abstract area of mathematical economics that aims to determine how a group of rational individuals can choose a correspondence while cooperating with each other. Lloyd Shapley is considered the leading architect of this branch of game theory by developing his main concepts in the 1950s and 1960s [55].

The foundations for the theoretical framework were established in 1962, when David Gale and Shapley Lloyd published a short article on a class of correspondence problems [54]. They considered a model of two sets of agents: workers and firms, which must be matched with each other. If a worker is hired by employer A, but this worker would have preferred employer B, who would also have liked to hire this worker (but did not do so), then there are untapped gains from this exchange. If employer B hired this worker, both would have had a better arrangement. Gale and Shapley proposed a delayed acceptance procedure that always leads to a stable match. The procedure shows how agents on one side of the market (e.g. employers) make offers to those on the other side, who accept or reject these
4 Stable marriage

offers according to certain rules.

The empirical relevance of this theory was later recognized by Alvin Roth in 1984 [53], Roth and Vate [56], Roth and Peranson [57]. Roth found that the US market for new resident doctors has always suffered from a series of failures due to the poor matching of residents to hospitals, and that a centralized clearinghouse has improved the situation by a procedure essentially equivalent to the delayed acceptance procedure of Gale and Shapley. Subsequently, Roth and his colleagues used this theory, in combination with empirical studies, controlled laboratory experiments, and computer simulations, to examine how other markets work [58]. Their research has not only informed the functioning of these markets, but has also proven useful in designing institutions that help markets work well, by implementing a version or extension of the Gale and Shapley procedure. This led to the emergence of a new and vigorous branch of the economy called "Market Design". The stable marriage problem and its variants have been extensively studied in combinatorial optimization and game theory [53]. In addition, as real applications, matching programs have been established in several areas, we can mention: organ donors to patients [59], CARMS (Canadian Resident Matching Service) in Canada [60] and JRMP (Japan Residency Matching Program) in Japan [61].

4.2 Principle

An SMP is a combinatorial problem. It consists in looking for a set of stable marriages between \( n \) men \( M = \{m_1, m_2, ..., m_n\} \) and \( n \) women \( W = \{w_1, w_2, ..., w_n\} \) (Fig II.1). Each individual has his or her Preference List \( PL \) where all members of the opposite sex appear sorted according to their affinity with them. If man prefers woman \( w \) to woman \( w' \), we write \( w >_m w' \) (Fig II.2).

![Figure II.1 – Stable marriage problem](image-url)
Problem: Create the couples man-woman the best possible according to their preferences.

A match $\mu$ is a subset of the $M \times W$ product where each person appears once and only once. If $(m, w) \in \mu$, then $m$ and $w$ form a matched pair in $\mu$ and $\mu(m) = w$ and $\mu(w) = m$. If $m$ and $w$ are not matched in $\mu$, then $(m, w)$ is an unpaired couple. $m$ and $w$ form a blocking pair if $m$ prefers $w$ to $\mu(m)$ and $w$ prefers $m$ to $\mu(w)$, but $m$ and $w$ form an unpaired couple in $\mu$ (Fig.II.3).

If the match contains no blocking pair, $\mu$ is a stable match.

Example

An example of SMP of size $n = 4$ appears in Table II.2 where men are labeled $m_1, m_2, m_3$ and $m_4$, women are labeled $w_1, w_2, w_3$ and $w_4$ and the following preference lists. Preference lists are in decreasing order, the most-preferred partner is on the left.

The matching $(m_1, w_4), (m_2, w_3), (m_3, w_2), (m_4, w_1)$ is stable. This matching is defined as a set of ordered pairs (man, woman) and its stability can be verified by considering
4 Stable marriage

| Men          | Women          |
|--------------|----------------|
| PL(m₁) : w₂, w₄, w₁, w₃ | PL(w₁) : m₂, m₁, m₄, m₃ |
| PL(m₂) : w₃, w₁, w₄, w₂ | PL(w₂) : m₄, m₃, m₁, m₂ |
| PL(m₃) : w₂, w₃, w₁, w₄ | PL(w₃) : m₁, m₄, m₃, m₂ |
| PL(m₄) : w₄, w₁, w₃, w₂ | PL(w₄) : m₂, m₁, m₄, m₃ |

Table II.2 – A SMP instance of size $n = 4$

Each man in turn as being a member of a blocking pair. The man $m₁$ can form a blocking pair with the woman $w₂$ he prefers to his partner $w₄$, but $w₂$ prefers his current partner $m₃$ to $m₁$. $m₂$ and $m₃$ are matched to their favorite women, so none of them can be in a blocking pair. Finally, $m₄$ can form a blocking pair with $w₄$, but she prefers to stay with her current partner $m₁$.

Another possible stable match is $(m₁, w₄), (m₂, w₁), (m₃, w₂), (m₄, w₃)$. The stability of this matching can be verified in the same way. On the other hand, the correspondence $(m₁, w₁), (m₂, w₂), (m₃, w₃), (m₄, w₄)$, for example, is unstable because of the blocking pair $(m₁, w₄)$. $m₁$ prefers $w₄$ to his current partner and reciprocally, $w₄$ prefers $m₁$ to his current partner. Other unstable matches may have more than one blocking pair; for example, the matching $(m₁, w₁), (m₂, w₂), (m₃, w₄), (m₄, w₃)$ has six blocking pairs: $(m₁, w₂), (m₁, w₄), (m₂, w₁), (m₂, w₄), (m₃, w₂), (m₄, w₄)$.

**Definition:**
Formally, we say that a marriage is stable iff:

- $\forall i, 1 \leq i \leq n$
- $M = \{m_i\}$ set of men
- $W = \{w_i\}$ set of women
- $\forall m_i, \exists PL(m_i) = W$
- $\forall w_i, \exists PL(w_i) = M$

$\nexists (m_i, w_i) \in M \cup W$ with $\mu(m) \neq w, w \succ_m \mu(m)$ and $m \succ_w \mu(w)$.

David Gale and Lloyd Shapley proved that, for any equal number of men and women, it is always possible to solve the SMP and make all marriages stable. They proposed the Gale-Shapley algorithm [54] (see Algorithm 1) to do so.
Algorithm 1 Gale-Shapley algorithm

1: Initialize all $m \in M$ and $w \in W$ to free
2: while $\exists$ free man $m$ who still has a woman $w$ to propose to do
3: $w =$ first woman on $m$’s list to whom $m$ has not yet proposed
4: if $w$ is free then
5: $(m, w)$ become engaged
6: else some pair $(m', w)$ already exists
7: if $w$ prefers $m$ to $m'$ then
8: $m'$ becomes free
9: $(m, w)$ become engaged
10: else
11: $(m', w)$ remain engaged
12: end if
13: end if
14: end while

4.3 Stable marriage problem in ridesharing

With regard to ridesharing systems, the problem of stable marriage is integrated in only one approach presented by Wang in [62]. Wang assumed that the number of passengers equals that of drivers and relied on the simplest approach of stable marriage defined by Gale and Shapley in [54]. However, in real life, considering such assumption is the furthest from the reality. For that, in our approach we associate the problem of stable marriage with the notion of stability in the matching problem but we rely on stable marriage assignment for unequal sets presented in [63]. Furthermore, the preference in his assumption solely depends on the potential financial benefits, i.e., the cost savings as compared to driving alone, where a higher saving implied a higher preference. In our approach, we incorporate personal preference to ensure social comfort when sharing a private space with others.

5 Conclusion

An exploratory study was conducted on ridesharing to better understand this alternative transportation by making a state of the art of these services, and focusing on some innovative academic work for modeling and optimization of such systems. This study has led us to define the major axes leading to the implementation of the foundations of our
5 Conclusion

approach. These main axes were, in fact, inspired by the problems and gaps that emerged from the study of existing approaches. A detailed description of our approach is then provided in the following chapter.
Chapter III

SMRM: A Stable Multi-Criteria Rideshare Matching

1 Introduction

In the previous chapter, we presented the theoretical foundations on which our contribution is based. In this chapter, we introduce SMRM, a Stable Multi-Criteria Rideshare Matching system. Indeed, SMRM selects the matches that promise the satisfaction of drivers and passengers’ social preferences, considering the notion of stability for rideshare matches.

In the second section of this chapter we illustrate the global idea of our approach. The entire process followed from the receipt of the first rideshare request to the generation of judgment matrices is detailed through the third section. The implementation details of the multi-criteria concept in our approach are then outlined in the level of the fourth section. Subsequently, the stable matching problem is described and formalized in section \[5\] Finally, section \[6\] summarizes and concludes this chapter.

2 System overview

2.1 Problematic

Although there are many attempts to provide a ridesharing system, they do not meet the expected success, given the lack of motivation of individuals to go to such systems. This lack of enthusiasm for this practice is explained in particular by the boredom of traveling with an unknown person. Indeed, for some, the car is a personal and intimate space, where he is free to do what he wants. In this sense, listening to the radio, singing
2 System overview

or phoning via a headset is akin to private activities, which we cannot or hardly share with others. Therefore, sharing a private space as the vehicle is not simple, especially if tastes and habits are different. Passengers and drivers often aspire to have a pleasant ridesharing time and this is not always the case if they come across people with different social characters. Everyone has their own personality and their moods, and instead of ensuring participants’ compatibility, classical ridesharing systems mainly focus on the improvement of their potential and performance in ridesharing to fulfill spatio-temporal constraints and to maximize certain objectives. In addition, a rideshare matching solution aiming to maximize the total system objective or the total number of matches may not necessarily maximize the objective of each individual participant.

2.2 Proposed approach

In this work, we introduce a new ridesharing system that we call SMRM, an acronym for Stable Multi-Criteria Rideshare Matching. SMRM avoids the drawbacks of previous approaches. Indeed, it selects the matches that promise the satisfaction of drivers and passengers’ social preferences, considering the notion of stability for rideshare matches. A matching is stable if there is no pair of participants who both prefer each other to their partners who are matched to.

2.2.1 Business case

A high-level scenario corresponding to the business case is shown in Fig. III.1. The business case assumes that a person wishing to reach a destination calls SMRM service, seeking for a correspondent being directed towards the same place subject to given personal constraints. The scenario can be either passenger-, or driver-initiated and evolves in seven main phases. Examining the passenger $P_i$ initiated scenario (for brevity, the description of the scenario initiated by the driver is omitted), in the first phase, he is prompted to register himself/herself providing their personal details such as name, date of birth, gender, status, telephone number... as well as additional personal profile attributes such as smoking, music, pet friendly and vehicle range. Afterward, $P_i$ is asked to complete a form indicating his personal preferences and the weight of each preference.
Remark:
In the case the user is already registered, he can immediately submit a trip offer or a trip request. On the other hand, a change of user’s profile is possible, the system will have to be able to update the appropriate parameters and adapt to the needs of the user. For
example, in the case where he wants to change his address or telephone number, he can update this information by himself.

SMRM computes in the first step the judgment matrices for all drivers that satisfy the spatio-temporal constraints of $P_i$. To do that, it accesses to the latter’s personal preferences, the weight of each preference, and the personal profile of each driver. Subsequently, according to these judgment matrices, SMRM evaluates the multiple constraints simultaneously, ranks possible matches for this passenger and provides their preference list where all drivers appear sorted according to their affinity with them. In the fifth phase, based on the preferences lists of all concerned users (passengers and drivers), the system returns the best possible pair according to their preferences. A pair of a stable matching in which there is no unmatched passenger and driver both prefer each other to their current correspondent. We suppose here that SMRM returns the driver $D_j$ as a correspondent of $P_i$. The sixth phase refers to the implementation of the trip, while the final phase, which takes place after the completion of the trip, consists in the feedback provided by both parties for future reference.

2.2.2 System Architecture

Fig. III.2 shows the architecture of the SMRM system, which consists of three main components: Preference Satisfier; Multi-Criteria Ranking; and Stable Matching. The three latter components are thoroughly described in the following.

Preference Satisfier: This component receives drivers and passengers’ preferences and then generates a judgment matrix for each user. This matrix represents the evaluation obtained from each correspondent with respect to the preferences of this utilizer. These matrices are computed based on preferences and weights of the user as well as on the profile and received evaluations of each correspondent.

Multi-Criteria Ranking: This component takes as an input the judgment matrices and matches after that each driver (resp. passenger) to a preferred list of passengers (resp. drivers). We formulate the problem as an MCDM problem and we adapt the Technique for Order Preference Similar to an Ideal Solution (TOPSIS) method as a correspondents ranking tool to evaluate the multiple constraints simultaneously.
Stable Matching: This component takes as an input a set of drivers $D$ and a set of passengers $P$ such that each driver $d \in D$ has a list of preferred passengers from $P$ and each passenger $p \in P$ has a list of preferred drivers from $D$. It returns a stable matching where there is no pair of participants who both prefer each other to the partners who they are matched to. After the completion of a ride, passengers and drivers could leave mutual feedback. The latter influences the computation of judgment matrices in the first component.

![Figure III.2 – SMRM architecture at a glance](image)

### 3 Preference Satisfier

This section develops the first component presented in Section 2.2.2 and shown in Fig. III.2 as well as its operation and interactions.

#### 3.1 User profile attributes

The attributes that represent the data associated with the user profile include identification data and matching judgment data. Identification data contain personal information about the user that makes it unique and identifiable by the system like CIN, surname, first name, phone, email, address, etc. Judgment data are necessary to judge the matching (provided in Table III.1), they contain information concerning the gender, the age, the
marital status, the vehicle range, whether the user is a smoker or not, whether he takes animals with him or not and whether he hears music or not. Other judgmental data are the social behavior, driving skills and reliability. This information is inferred through the evaluation procedure in the system. This procedure is carried out by the drivers concerning passengers and vice versa at the end of each trip. It offers users (the driver and the passenger) the opportunity to complete a short questionnaire, evaluating the correspondent. The questions aim to extract the user’s opinion of these parameters.

| attribute          | Notation       | Source    | Value                 | User                  |
|--------------------|----------------|-----------|-----------------------|-----------------------|
| Gender             | Gender         | Input     | M / F                 | Passenger & Driver    |
| Age                | Age            | Input     | Integer > 18          | Passenger & Driver    |
| Marital status     | Status         | Input     | Married / single      | Passenger & Driver    |
| Vehicle range      | VHrange        | Input     | Basic / Comfort / Luxury | Driver                |
| Pet friendliness   | Pets           | Input     | Yes / No              | Passenger & Driver    |
| Listening to music | Music          | Input     | Yes / No              | Passenger & Driver    |
| Smoking habit      | Smoking        | Input     | Yes / No              | Passenger & Driver    |
| Social behavior    | SocialBehavior | Feedback  | [0..10]               | Passenger & Driver    |
| Driving skills     | DrivingSkills  | Feedback  | [0..10]               | Driver                |
| Reliability        | Reliability    | Feedback  | [0..10]               | Passenger & Driver    |

Table III.1 – Judgment data

It is important to make evaluation easily understandable and factual for users, and it is the system that converts each evaluation category into a score. In this way, after each trip, the system updates this information by assigning the score of the evaluation and calculating the new obtained average. This information makes it possible to create more successful matches in the future. The evaluation attributes, their potential values and
their corresponding scores are summarized in Table III.2.

| attribute       | Value          | Score |
|-----------------|----------------|-------|
| SocialBehavior  | Friendly 10    |       |
|                 | Polite 5       |       |
|                 | Rude 0         |       |
| DrivingSkills   | Efficient 10   |       |
|                 | Acceptable 5   |       |
|                 | Dangerous 0    |       |
| Reliability     | Extremely reliable 10 | |
|                 | moderately Reliable 5 | |
|                 | Not reliable 0 |       |

Table III.2 – Evaluation attributes

Remark:
Vehicle range and driving skills data are optional, since a system user may not own a car, but may only use the SMRM service as a passenger.

3.2 User preference attributes

Social constraints are important to define and agree between users. In this respect, passengers and drivers are asked to indicate their personal preferences. The attributes that represent the preferences associated with the correspondent are the age, the gender, the marital status, the vehicle range, smoking habit, pet friendliness, listening to music. More specifically, each user indicates the preferred age, as well as the age tolerance range in which he wishes his correspondent to be. Usually, the gender of the user makes no difference, but sometimes the gender can help people to have common interests so the chance of having something to discuss increases and makes the trip more enjoyable. Being married or single affects at a large extent whether the user will accept a match or not. For example, mothers may have many common interests in their children, which they could not have done by traveling with a single person. Smoking habit can be a very important parameter for a user and being in agreement on this point creates higher possibility for successful journey.

Shared music preferences create and intensify social bonds and finally leads to the social attraction. Indeed, listening to music and talking about one’s favorite music is a great
3 Preference Satisfier

conversation starter when meeting new people. Pet friendliness is also a factor that influences the users’ correspondence and their ability to make a pleasant trip. Participant’s concern about vehicle range is because people tend to be in a comfortable and convenient atmosphere when traveling which affects the acceptance of correspondence.

With regard to social behavior, driving and reliability attributes, the user also specifies his weight but he does not attribute a value of preference. This means that the user is able to indicate the level of interest on this attribute, or it does not matter to him.

A summary of the user preference attributes is provided in Table III.3.

| Attribute                  | Notation         | Value                      | User               |
|----------------------------|------------------|----------------------------|--------------------|
| Gender                     | GenderPref       | M / F                      | Passenger & Driver |
| Age                        | AgePref          | Integer > 18              | Passenger & Driver |
| Age tolerance              | AgeTolerance     | [1..20]                    | Passenger & Driver |
| Marital status             | StatusPref       | Married / single           | Passenger & Driver |
| Vehicle range              | VHrangePref      | Basic / Comfort / Luxury   | Passenger          |
| Pet friendliness           | PetsPref         | Yes / No                  | Passenger & Driver |
| Listening to music         | MusicPref        | Yes / No                  | Passenger & Driver |
| Smoking habit              | SmokingPref      | Yes / No                  | Passenger & Driver |
| Social behavior            | SocialBehaviorPref | Not indicated             | Passenger & Driver |
| Driving skills             | DrivingSkillsPref | Not indicated             | Passenger          |
| Reliability                | ReliabilityPref  | Not indicated             | Passenger & Driver |

Table III.3 – User preference attributes

3.3 User weight attributes

In addition to the above attributes, a SMRM user must specify the importance that he assigns to each of his preferences. This is achieved by assigning each attribute with a
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certain weight. Of course, it is possible that the attributes have the same weight for the user. For example, a user may consider just as important that his passenger listens to music, as well as whether he is married or not. Practically, the user assigns each attribute a value between 0 and 10, 0 meaning that the user ignores this preference and 10 pointing for great importance. In the case where a attribute has the same weight with another (or more than one) attribute, it is deduced that the user has an equal interest in these attributes.

The attributes that represent the weight vector are the age, the gender, the marital status, the vehicle range, smoking habit, pet friendliness, listening to music, social behavior, driving skills and reliability.

The following table presents these attributes.

| Attribute          | Notation      | User               |
|--------------------|---------------|--------------------|
| Gender             | GenderW       | Passenger & Driver |
| Age                | AgeW          | Passenger & Driver |
| Marital status     | StatusW       | Passenger & Driver |
| Vehicle range      | VHrangeW       | Passenger          |
| Pet friendliness   | PetsW         | Passenger & Driver |
| Listening to music | MusicW        | Passenger & Driver |
| Smoking habit      | SmokingW      | Passenger & Driver |
| Social behavior    | SocialBehaviorW | Passenger & Driver |
| Driving skills     | DrivingSkillsW | Passenger          |
| Reliability        | ReliabilityW  | Passenger & Driver |

Table III.4 – User weight attributes

3.4 Judgment matrix

The preference satisfier component computes driver/passenger profiles and preferences then represents them into a judgment matrix for each user. It takes as input a set $D$ of $n$ drivers and a set $P$ of $m$ passengers. Each driver $d \in D$ (resp. passenger $p \in P$) has a profile vector $prof(d)$ (resp. $prof(p)$) and a preference vector $pref(d)$ (resp. $pref(p)$), in addition to the corresponding weight of each preference $w(d)$ (resp. $w(p)$). The attributes of $prof$, $pref$ and $w$ vectors are illustrated in Table II.5.

The judgment matrix of a driver $d$ is noted $X(d) = (x_{ij}) m \times k$ (in our case $k = 8$) where
Table III.5 – Attributes of prof, pref and w vectors of drivers and passengers

| Vector | Attributes |
|--------|------------|
| prof(d) | Gender, Age, Status, VHrange, Pets, Smoking, Music, SocialBehavior, DrivingSkills, Reliability |
| prof(p) | Gender, Age, Status, Pets, Smoking, Music, SocialBehavior, Reliability |
| pref(d) | GenderPref, AgePref, StatusPref, PetsPref, SmokingPref, MusicPref, SocialBehaviorPref, ReliabilityPref |
| pref(p) | GenderPref, AgePref, StatusPref, VHrangePref, PetsPref, SmokingPref, MusicPref, SocialBehaviorPref, DrivingSkillsPref, ReliabilityPref |
| w(d) | GenderW, AgeW, StatusW, PetsW, SmokingW, MusicW, SocialBehaviorW, ReliabilityW |
| w(p) | GenderW, AgeW, StatusW, VHrangeW, PetsW, SmokingW, MusicW, SocialBehaviorW, DrivingSkillsW, ReliabilityW |

rows represent passengers, columns represent driver d preferences and \( x_{ij} \) is the score of passenger \( p_i \) with respect to the driver preference \( j \). Respectively, the judgment matrix of a passenger \( p \) is noted \( X(p) = (x_{ij}) \ n \times l \) (in our case \( l = 10 \)) where rows represent drivers, columns represent passenger \( p \) preferences and \( x_{ij} \) is the score of driver \( d_i \) with respect to the passenger preference \( j \).

The values \( x_{ij} \) of \( X(d) \) and \( X(d) \) are computed using the following functions:

- **Binary_Score(i,j):** if the preference \( j \) is a GenderPref, StatusPref, PetsPref, SmokingPref, MusicPref or VHrangePref.

- **Age_Score(i,j):** if the preference \( j \) is an AgePref.

- **Feedback_Score(i,j):** if the preference \( j \) is a SocialBehaviorPref, DrivingSkillsPref or ReliabilityPref.

**Definition 1.** (Binary_Score): Let \( Pref_j \) be a preference of a driver \( d \) (resp. passenger \( p \)) and \( Prof_j \) be the correspondent profile input of a passenger \( p_i \) (resp. driver \( d_i \)), we define Binary_Score as follows:

\[
Binary_Score(i, j) = \begin{cases} 
1 & \text{if } Pref_j = Prof_j \\
0 & \text{otherwise} 
\end{cases}
\]
Definition 2. (Age_Score): Let $AgePref$ be the age preference of a driver $d$ (resp. passenger $p$) and $AgeTolerance$ its age tolerance. Let $Age$ be the age of a passenger $p_i$ (resp. driver $d_i$). We define $Age_Score$ as follows:

$$Age_Score(i, j) = \frac{AgeTolerance}{|Age - AgePref| + T}$$

Definition 3. (Feedback_Score): is the average evaluations $e_i$ ($i = 1, ..., n$) received from drivers or passengers according to their previous experiences.

$$Feedback_Score(i, j) = \frac{\sum_{i=1}^{n} e_i}{n}$$

Illustrative example

We consider a passenger $P_1$ and six drivers $D_1, ..., D_6$ making a ridesharing requests that fulfill the spatio-temporal constraints of $P_1$ request. $P_1$ is supposed to have already filled his personal profile and his preferences about preferred drivers and also stating the weights of each preference. Table III.6 draws $P_1$ preferences and their respective weights. Similarly, we suppose that all drivers have already provided their personal details or profile as shown in Table III.7.

| Preferences       | Pref(P1) | Weights       | w(P1) |
|-------------------|----------|---------------|-------|
| GenderPref        | M        | GenderW       | 4     |
| AgePref           | 30       | AgeW          | 9     |
| StatusPref        | Single   | StatusW       | 6     |
| VHrangePref       | Comfort  | VHrangeW      | 5     |
| PetsPref          | Yes      | PetsW         | 0     |
| MusicPref         | No       | MusicW        | 8     |
| SmokingPref       | No       | SmokingW      | 8     |
| SocialBehaviorPref| -        | SocialBehaviorW| 6     |
| DrivingSkillsPref | -        | DrivingSkillsW| 7     |
| ReliabilityPref   | -        | ReliabilityW  | 0     |

| AgeTolerance | 5 |

Table III.6 – Preferences and weights vector of passenger $P_1$
In the sequel, the PreferenceSatisfier component is responsible for computing the judgment matrix of passenger \( P_1 \), \( X(P_1) = (x_{ij}) \) 6 \( \times \) 10, based on his preferences presented in Table III.6 and the profile of each driver provided in Table III.7.

Table III.7 – Profile vectors of drivers

| Profiles | Gender | Age | Status | VH range | Pets | Music | Smoking | Social Behavior | Driving Skills | Reliability |
|----------|--------|-----|--------|----------|------|-------|---------|----------------|----------------|-------------|
| Prof(D1) | M      | 26  | Married| Luxury   | No   | Yes   | Yes     | 4.77           | 4.12           | 7.78        |
| Prof(D2) | F      | 44  | Married| Basic    | Yes  | No    | Yes     | 1.06           | 5.94           | 6.39        |
| Prof(D3) | F      | 34  | Single | Basic    | No   | No    | Yes     | 5.58           | 9.3            | 6.46        |
| Prof(D4) | M      | 65  | Single | Luxury   | No   | No    | No      | 0.34           | 4.34           | 0.23        |
| Prof(D5) | M      | 38  | Single | Comfort  | Yes  | Yes   | No      | 4.37           | 1.63           | 8.65        |
| Prof(D6) | F      | 49  | Married| Comfort  | Yes  | Yes   | Yes     | 3.08           | 8.91           | 1.88        |

Table III.8 depicts the generated judgment matrix of passenger \( P_1 \). In this matrix, \( x_{11} = \text{Binary\_Score}(1,1) = 1 \) since the gender preference of passenger \( P_1 \) (Male) is equal to the gender profile of the driver \( D_1 \) (Male). Also, \( x_{12} = \text{Age\_Score}(1,2) = \frac{\text{AgeTolerance}}{|\text{Age} - \text{AgePref}| + \text{AgeTolerance}} = \frac{5}{|26 - 30| + 5} = 0.55 \). It is important to note that SocialBehaviorPref, DrivingSkillsPref and ReliabilityPref derive from the evaluations the driver \( D_1 \) has received in the previous matches and their values do not depend on passenger preferences.

4 Multi-Criteria Ranking

MCDM is a branch of operation research models, which is suitable for solving an issue featuring a high number of decision criteria, different forms of information, multi-interests and perspectives, and conflicting objectives [33]. In the dedicated literature, there are dozens of methods used for solving MCDM problems such as the analytical hierarchy process, TOPSIS, the elimination and choice translating reality, the preference ranking organization method for enrichment evaluation, the compromise programming, and the multi-attribute utility theory, to cite but a few.

The TOPSIS method can be considered as one of the most widely accepted variants. The basic concept of TOPSIS is to find the best compromise solution according to the
Table III.8 – The generated judgment matrix of passenger $P_1$

designer’s objective weights. This method attempts to choose the alternatives that simultaneously have the shortest Euclidean distance from the positive ideal solution and the furthest Euclidean distance from the negative ideal solution. The ideal solution is composed of all attainable best attribute values; the negative ideal solution is composed of all attainable worst attribute values. TOPSIS, therefore, provides a cardinal ranking for all the alternatives by taking the relative closeness to the ideal solution.

In our case we adapt the TOPSIS method to rank possible matches for each user (driver and passenger) according to their preferences.

Formally, for each driver $d$ (passenger $p$), we have a ranking problem with $m$ alternatives $P_i (i = 1,...,m)$ evaluated on $k$ criteria $C_j (j = 1,...,k)$ ($n$ alternatives $D_i (i = 1,...,n)$ evaluated on $l$ criteria $C_j (j = 1,...,l)$). The proposed procedure can be expressed for each driver $d$ in the following steps [64].

The input is the judgment matrix $X(d) = (x_{ij})$ $m \times k$ generated by the first component and defined as follows:

$$X(d) = \begin{pmatrix}
\text{Pref}_1 & \text{Pref}_2 & \ldots & \text{Pref}_j & \ldots & \text{Pref}_k \\
\text{p}_1 & x_{11} & x_{12} & \ldots & x_{1j} & \ldots & x_{1k} \\
\text{p}_2 & x_{21} & x_{22} & \ldots & x_{2j} & \ldots & x_{2k} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\text{p}_1 & x_{11} & x_{12} & \ldots & x_{1j} & \ldots & x_{1k} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\text{p}_m & x_{m1} & x_{m2} & \ldots & x_{mj} & \ldots & x_{mk}
\end{pmatrix}$$

The proposed procedure can be expressed for each driver $d$ in the steps presented in the
4 Multi-Criteria Ranking

following figure [64].

Figure III.3 – Stepwise procedure for performing TOPSIS methodology

4.1 Step 1: Normalized decision matrix

This process transforms the attribute dimensions into non dimensional attributes, which allows comparing across attributes. The normalized decision matrix $R(d)$ can be computed with the help of Eq.III.1.

$$ r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} (x_{ij}^2)}} \text{ for } i = 1, ..., m; j = 1, ..., k $$ (III.1)

The pseudo code of this step is shown in Algorithm 1

Fig.III.4 shows the result of this step on the matrix example expressed in Table III.8

4.2 Step 2: Weighted normalized decision matrix

The set of weights $w(d) = (w_1, w_2, ..., w_d)$ from the driver, as presented in Table II.1, is accommodated to the decision matrix in this step. The weighted normalized decision matrix is computed by multiplying each column of the matrix $R$ with its associated weight $w_j$ as given in Eq.III.2

$$ v_{ij} = w_j * r_{ij} \text{ for } i = 1, 2, ..., m; j = 1, ..., k $$ (III.2)
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Algorithm 2 TOPSIS

1: function STEP_1(X, m, k)
2: Initialize T = Totals vector of size k
3: Initialize R = Normalized decision matrix of size m * k
4: for j = 1 → k do
5: for i = 1 → m do
6: \[ T[j] += X[i][j]^2 \]
7: end for
8: end for
9: for i = 1 → m do
10: for j = 1 → k do
11: \[ R[i][j] = X[i][j] / \sqrt{T[j]} \]
12: end for
13: end for
14: return R
15: end function

The pseudo code of this step is shown in Algorithm 3.

Fig. III.5 shows the result of this step on the matrix example expressed in Fig. III.4.

4.3 Step 3: Positive ideal and negative ideal solutions

Two artificial alternatives \( A^* \) and \( A^- \) indicating the most preferable alternative (positive ideal solution) and the least preferable one (negative-ideal solution) are respectively defined as:

\[ A^* = \{v^*_1, v^*_2, \ldots, v^*_j, \ldots, v^*_k\} = \{max_{ij}(v_{ij})| \ i = 1, \ldots, m; \ j = 1, \ldots, k\} \] (III.3)

\[ A^- = \{v^-_1, v^-_2, \ldots, v^-_j, \ldots, v^-_k\} = \{min_{ij}(v_{ij})| \ i = 1, \ldots, m; \ j = 1, \ldots, k\} \] (III.4)
4 Multi-Criteria Ranking

Algorithm 3 TOPSIS

1: function STEP_2(R, W, m, k)
2: Initialize V = Weighted normalized decision matrix of size \( m \times k \)
3: for \( i = 1 \rightarrow m \) do
4:     for \( j = 1 \rightarrow k \) do
5:         \( V[i][j] = R[i][j] \times W[j] \)
6:     end for
7: end for
8: return \( V \)
9: end function

Figure III.5 – Construction of weighted normalized decision matrix

The pseudo code of this step is shown in Algorithm 1.

Fig. III.6 shows the result of this step on the matrix example expressed in Fig. III.6

4.4 Step 4: Separation measures

The separation between each alternative can be measured by the Euclidean distance. The separation of each alternative from the ideal one is then given by:

\[
S^*_{i} = \sqrt{\sum_{j=1}^{k} (v_{ij} - v^*_{j})^2} \quad \text{for } i = 1, ..., m \quad (III.5)
\]
Algorithm 4 TOPSIS

1: function STEP_3(S, V, m, k)
2:     if S == 0 then
3:         Initialize P = Positive Ideal vector of size k
4:         for j = 1 → k do
5:             Initialize P[j] = 0
6:             for i = 1 → m do
7:                 if V[i][j] > P[j] then
8:                     P[j] = V[i][j];
9:             end if
10:         end for
11:     end for
12:     return P
13: else
14:     Initialize N = Negative Ideal vector of size k
15:     for j = 1 → k do
16:         Initialize N[j] = 10
17:         for i = 1 → m do
18:             if V[i][j] < N[j] then
19:                 N[j] = V[i][j];
20:         end if
21:     end for
22:     return N
23: end if
24: end function
4 Multi-Criteria Ranking

Similarly, the separation from the negative-ideal one can be derived using the following equation:

\[ S_i^− = \sqrt{\sum_{j=1}^{k} (v_{ij} - v_{ij}^-)^2} \text{ for } i = 1, ..., m \] (III.6)

The pseudo code of this step is shown in Algorithm 1.

We call the same function with the parameter N instead of parameter P to compute the separation from the negative-ideal alternative. Fig. III.7 shows the result of this step on the solution example expressed in Fig. III.6.

Algorithm 5 TOPSIS
1: function STEP_4(V, P, m, k)
2: Initialize PS = Positive Separation vector of size m
3: for \( i = 1 \rightarrow m \) do
4: for \( j = 1 \rightarrow k \) do
5: \( PS[i]^+ = (V[i][j] - P[j])^2 \);
6: end for
7: \( PS[i] = \sqrt{S[i]} \);
8: end for
9: return PS
10: end function

4.5 Step 5: Preference order

A set of alternatives can now be ranked by preference through the computation of the relative closeness to the ideal value solution \( C_i^* \) utilizing the following equation:

\[ C_i^* = \frac{S_i^-}{(S_i^+ + S_i^-)} \text{ for } i = 1, ..., m \] (III.7)
These preference lists are afterwards used to compute the stable matching. The pseudo code of this step is shown in Algorithm 6.

Algorithm 6 TOPSIS

1: function STEP_5(PS, NS, m)
2: Initialize C = Closeness to the ideal solution vector of size m
3: for i = 1 → m do
4: \[ C[i] = NS[i] / (NS[i] + PS[i]) \]
5: end for
6: return C
7: end function

Fig. III.8 shows the result of this step on the solution example expressed in Fig. III.7. Finally, through ranking these values, we obtain the preference list of passenger P1. \( PL(P_1) = D_5, D_3, D_4, D_1, D_2, D_6 \).

5 Stable Matching

The ridesharing problem is treated as a matching problem where drivers are assigned to passengers. Our objective, in this phase, is to create a perfect matching of drivers and passengers such that there does not exists any pair of a driver and a passenger who prefers each other to their current partners. If a passenger and a driver form such a pair, they are called a blocking pair. If there are no blocking pairs in the matching solution, we call it a stable rideshare matching.
5 Stable Matching

5.1 Satisfaction of users’ preferences

Classical ridesharing systems mainly focus on the improvement of their potential and performance in ridesharing to maximize certain objectives. Indeed, they propose a matching solution that maximizes the total system objective or the total number of matches. Nevertheless, such a solution may not necessarily maximize the objective of each individual participant, and may subsequently be rejected by the participants. Even if a proposed match satisfies a participant’s constraints, a passenger and/or driver may not accept a match if they believe they can establish a better one.

Example

Table III.9 and Table III.10 show an illustrative example of 3 passengers and 6 drivers. We assume that after running the multi-criteria ranking component, we obtain the result shown in Table III.9 where $C^*_i$ (the relative closeness to the ideal value solution) is computed for each pair driver / passenger. Through ranking these values, we obtain also the preference list of each user as shown in Table III.10.

The system-optimal solution is to assign passenger $P_1$ to driver $D_1$, passenger $P_2$ to driver $D_2$ and passenger $P_3$ to driver $D_3$. This would result in a system-wide objective of 4.3, an individual objective of 0.5 for $P_1$ and an individual objective of 0.7 for $D_2$.

However, $P_1$ prefers $D_2$ to his current partner ($D_1$) and $D_2$ prefers $P_1$ to his current partner ($P_2$). So, $(P_1, D_2)$ form a blocking pair as they would both prefer to be matched
Table III.9 – $C^*$ of the users

| Passengers | Drivers |
|------------|---------|
| $PL(P_1) : D_2, D_1, D_5, D_3, D_6, D_4$ | $PL(D_1) : P_1, P_3, P_2$ |
| $PL(P_2) : D_2, D_3, D_1, D_6, D_1, D_5$ | $PL(D_2) : P_1, P_2, P_3$ |
| $PL(P_3) : D_6, D_3, D_4, D_5, D_1, D_2$ | $PL(D_3) : P_3, P_2, P_1$ |
| $PL(D_4) : P_1, P_2, P_3$ | $PL(D_5) : P_2, P_1, P_3$ |
| $PL(D_6) : P_3, P_2, P_1$ | $PL(D_6) : P_3, P_2, P_1$ |

Together instead of to their current partners. If they were matched, it would increase their individual goals by 0.2.

### 5.2 Problem Formulation

Formally [65], let $D = \{d_1, d_2, ..., d_n\}$ be a set of drivers. Let $P = \{p_1, p_2, ..., p_m\}$ be a set of passengers. A matching is a one-to-one mapping $\mu$ from $D \cup P$ to itself, such that:

1. $\mu(d) = p$ if and only if $\mu(p) = d$, in which case $d$ is matched to $p$;
2. If $\mu(d)$ is not in $P$, then $\mu(d) = d$, in which case $d$ is unmatched;
3. If $\mu(p)$ is not in $D$, then $\mu(p) = p$, where case $d$ is unmatched.

We also define the notation for preference as the form $p_1 \succ_d p_2$ denotes that driver $d$ prefers passenger $p_1$ to $p_2$.

A matching $\mu$ is a stable matching if it contains no blocking pairs. A blocking pair is defined as a pair $(d, p) \in D \cup P$ with $\mu(d) \neq p, p \succ_d \mu(d)$ and $d \succ_p \mu(p)$. Let $A$ denote the
set of acceptable pairs. The incidence vector of a matching $\mu$ is a vector $x \in \{0, 1\}^{\left|D\right| \times \left|P\right|}$ such that $x_{d,p} = 1$ if $\mu(d) = p$. Otherwise, $x_{d,p} = 0$. We identify each matching with its incidence vector. A vector $x \in \mathbb{N}^{\left|D\right| \times \left|P\right|}$ is a stable matching if and only if it is an integer solution of the following system of linear equations:

$$\sum_{j \in P} x_{d,j} \leq 1 \text{ for each } d \in D$$  \hspace{1cm} (III.8)

$$\sum_{i \in D} x_{i,p} \leq 1 \text{ for each } p \in P$$  \hspace{1cm} (III.9)

$$x_{d,p} \geq 0 \text{ for each } (d, p) \in D \times P$$  \hspace{1cm} (III.10)

$$x_{d,p} = 0 \text{ for each } (d, p) \in (D \times P) \setminus A$$  \hspace{1cm} (III.11)

$$\sum_{j \succ_{d} p} x_{d,j} + \sum_{i \succ_{p} d} x_{i,p} + x_{d,p} \geq 0 \text{ for each } (d, p) \in A$$  \hspace{1cm} (III.12)

Constraints (8), (9), and (10) represent matching constraints. Constraint (11) is called \textit{individual rationality constraint}. Constraint (12) defines the stability constraints. It ensures that for each acceptable pair $(d, p)$, either driver $d$ is corresponding to someone they prefer to passenger $p$, or $p$ is corresponding to someone they prefer to $d$, or $d$ and $p$ are corresponding to each other.

### 5.3 Stable marriage solutions

For any given sets $P$ and $D$ there are in general several stable marriage solutions. According to the work of [63], the stability of the matching is defined on one of the following three solutions:

1. Driver optimal stable solution, which is optimal from the drivers’ point of view. This is the stable matching when there are no other stable solutions in which each driver is matched with the same passenger or with a passenger they prefer to their partner.

2. Passenger optimal solution, which is optimal from the passengers’ point of view. This is the stable matching when there are no other stable solutions in which each passenger is matched with the same driver or with a driver they prefer to their partner.

3. The minimum choice solution, which is optimal from the less numerous set’s point of view. This is the stable matching when the less numerous set get their best possible choices. Thus, if there are fewer drivers than passengers, the driver optimal solution is obtained. However, if there are more drivers than passengers, the passenger optimal solution is obtained.
Example

Fig. III.9 presents stable marriage solutions for the lists of preferences given in Table III.10. The matching 
$$(P_1, D_2), (P_2, D_1), (P_3, D_3)$$ give a stable marriage since only one 
driver $D_1$ would consider another matching an improvement ($P_2$ or $P_3$), however passenger 
$P_1$ prefers driver $D_2$ to driver $D_1$ and passenger $P_3$ prefers driver $D_3$ to driver $D_1$. This 
is in fact the driver optimal stable solution. The other stable marriage is given by the 
matching $$(P_1, D_2), (P_2, D_3), (P_3, D_6)$$ and this is the passenger optimal stable solution. 
Only one passenger $P_2$ would consider the matching with driver $D_2$ an improvement, but 
driver $D_2$ prefers passenger $P_1$ to passenger $P_2$. The minimum choice solution is the 
passenger optimal stable solution since there are fewer passengers than drivers.

| Driver optimal stable solution | $(P_1, D_2), (P_2, D_1), (P_3, D_3)$ |
|-------------------------------|-------------------------------------|
| Passenger optimal stable solution | $(P_1, D_2), (P_2, D_3), (P_3, D_6)$ |
| Minimum choice solution       | $(P_1, D_2), (P_2, D_3), (P_3, D_6)$ |

Figure III.9 – Stable marriage solutions

5.4 Proposed algorithm

The driver optimal solution works well when there are fewer drivers than passengers. However, when the drivers are more numerous, several drivers will have to exhaust their preference lists since they will not be chosen by any passenger and will be the drivers who end up unmatched. With the same reasoning, the passenger optimal solution works well when there are fewer passengers than drivers.

We opt then for the minimum choice solution which is clearly a more efficient solution for finding a stable matching. Thus, if there are fewer drivers than passengers, the drivers’ optimal solution is reached. Nevertheless, if there are more drivers than passengers, the passengers’ optimal solution is obtained. To find this solution and make all matches stable, we rely on the SM algorithm given in Algorithm 7.
Algorithm 7 SM algorithm

1: procedure SM(driverchoice, passengerchoice, matching, n, k)
2:   Initialize menlarger = n > k
3:   if menlarger then
4:     max = k
5:     min = n
6:   else
7:     max = n
8:     max = n
9:   end if
10:  Initialize chno matrix of integer of size min * max
11:  Initialize counter vector of 0 of size min
12:  for i = 1 → min do
13:      for j = 1 → max do
14:         if menlarger then
15:            chno[i][passengerchoice[i][j]] = j
16:         else
17:            chno[i][driverchoice[i][j]] = j
18:         end if
19:      end for
20:  end for
21:  for i = 1 → min do
22:      if menlarger then
23:          PROPOSAL(i, passengerchoice, matching, counter, chno)
24:      else
25:          PROPOSAL(i, driverchoice, matching, counter, chno)
26:      end if
27:  end for
28: end procedure
Procedure \( SM(driverchoice, passengerchoice, matching, n, k) \) finds a single stable matching (SM). There are \( n \) drivers and \( k \) passengers, and the smaller set proposes. The optimal stable solution for the smaller set is obtained. The result is left in the integer array matching. Thus \( matching[i] \) is the driver whom the \( i-th \) passenger is matched to if \( n < k \), but if there are less passengers then \( marriage[i] \) is the passenger whom the \( i-th \) drivers is matched to. If \( matching[i] = 0 \) at the end then that person is unmatched. There will be \( |n - k| \) elements of matching zero. \( driverchoice \) and \( passengerchoice \) are the choice matrices for the drivers and the passengers respectively, i.e. \( driverchoice[i, j] \) is the \( j-th \) choice of the \( i-th \) driver. The formal integer arrays should have the following sizes, \( driverchoice[1:n, 1:k], passengerchoice[1:k, 1:n], matching[1:max(n, k)] \);

Procedure \( PROPOSAL(i, choice) \) (Algorithm 8) makes the next proposal for driver/passenger \( i \), and calls the procedure \( REFUSAL \) to see what effect this proposal will have. The procedure does nothing if driver/passenger is the dummy 0.

Procedure \( REFUSAL(i, j, choice) \) (Algorithm 9) decides which of the two proposals, the one being kept in suspense or the one just received, should be retained. Whichever is rejected goes back to the procedure \( PROPOSAL \) to make the next proposal.

Fig. III.10 shows an illustrative example of the execution of this algorithm on the stable marriage instance of 4 passengers and 3 drivers presented in Table III.11.

| Passengers       | Drivers       |
|------------------|---------------|
| \( PL(P_1) \) : D_2, D_1, D_3 | \( PL(D_1) : P_1, P_3, P_4, P_2 \) |
| \( PL(P_2) \) : D_2, D_3, D_1 | \( PL(D_2) : P_1, P_4, P_2, P_3 \) |
| \( PL(P_3) \) : D_3, D_2, D_1 | \( PL(D_3) : P_3, P_4, P_2, P_1 \) |
| \( PL(P_4) \) : D_1, D_2, D_3 |               |

Table III.11 – Stable marriage instance of 4 passengers and 3 drivers
6 Conclusion

Algorithm 9 SM algorithm
1: procedure REFUSAL(i, j, choice, matching, counter, chno)
2: Initialize l integer
3: if matching[j] == 0 then
4: matching[j] = i
5: else
6: if chno[j][matching[j]] > chno[j][i] then
7: l = matching[j]
8: matching[j] = i
9: PROPOSAL(l, choice, matching, counter, chno)
10: else
11: PROPOSAL(i, choice, matching, counter, chno)
12: end if
13: end if
14: end procedure

6 Conclusion

In this chapter, we have suggested SMRM, a system that promises the satisfaction of drivers and passengers’ social preferences, considering the notion of stability for rideshare matches. The tasks associated with the SMRM system have been divided into three components each of which has a specific role for the optimization of the service as a whole.

The following chapter details the different tools used in the development of our system. The performed experimentations to assess our system are then discussed.
| Step 1 | 1 | 2 | 3 | 4 |
|--------|---|---|---|---|
| 0      | 0 | 0 | 0 | 0 |

| Step 2 | 1 | 2 | 3 | 4 |
|--------|---|---|---|---|
| 1      | 0 | 0 | 0 | 0 |

| Step 3 | 1 | 2 | 3 | 4 |
|--------|---|---|---|---|
| 2      | 0 | 0 | 0 | 0 |

| Step 4 | 1 | 2 | 3 | 4 |
|--------|---|---|---|---|
| 2      | 0 | 1 | 0 |   |

| Step 5 | 1 | 2 | 3 | 4 |
|--------|---|---|---|---|
| 2      | 0 | 3 | 0 |   |

| Step 6 | 1 | 2 | 3 | 4 |
|--------|---|---|---|---|
| 2      | 0 | 3 | 1 |   |

**Matching table**

Figure III.10 – Execution of the SM algorithm
Chapter IV

Experimental Results

1 Introduction

The main concepts related to our proposal have been defined, this chapter concretizes all these concepts thus providing the pragmatic level required for the validation of our approach.

All basic concepts and fundamentals related to the development phase, including implementation and testing, are described. We will first present a brief summary of the aspects related to our method of resolution. A description of the experimental environment will be the subject of the third section. The last section of this chapter will discuss the different execution results.

2 Areas of scientific interests

In order to restore the balance between the improvement aspect and the satisfaction requirements from a practical point of view, we were able to consider several theoretical concepts as well as the necessary tools to benefit from them. A methodological and strategic choice was thus the result of efforts expended in this direction by a research team for the elaboration of this master in the LIPAH laboratory. Our work was then oriented in this direction and resulted in a combination of scientific fields.

We thus classify our work as a meeting point of varied and highly evolved domains. Indeed, the approach we have reached uses different concepts. These latter are implemented by the different steps developed for the achievement of our objectives, each step involves one or more areas of interest.

These lead on the whole to a decision support system making use of artificial intelligence
to search for stable matching in a dynamic ridesharing context in favor of the realization of the sustainable development project (Fig. IV.1).

![Diagram showing various scientific fields related to SMRM]

Figure IV.1 – SMRM: A wide range of scientific fields

3 Experimental environment

In this section we detail the different tools and data used as well as the evaluation metrics for the testing of our application.

3.1 Implementation

To devaluate the impact of stability on system performance, we test two different implementations on an Intel Core i5 Linux machine with 8GB RAM: one with the SM algorithm implemented in Java, and the other, with CPLEX interface with Java as a linear and binary integer programming solver to find the optimal solution for unconstrained matching (A), i.e. relaxing constraint (3.12).
3 Experimental environment

CPLEX
In order to implement an optimal linear assignment solution, we used CPLEX interface with Java. The latter favors the resolution of real-world assignment problems. It contains a robust optimizer that handles the side constraints that are invariably found in all types of problems. For pure academic problems, it finds solutions that are comparable to solutions found by specialized algorithms. Certain combinatorial optimization problems cannot be easily linearized and solved with traditional mathematical programming methods. To handle these problems, it provides a large set of arithmetic and logical constraints, as well as a robust optimizer that brings all the benefits of a model-and-run development process to combinatorial optimization.

3.2 Evaluation metrics

To evaluate the choice of our solution for the multi-criteria evaluation, we compare the head of the preference list of our approach to that of the approach of our competitors. For this, we use a metric that compares the total weight of preferences where the head of the list exceeds its competitor of the other approach. We define the Weight Superiority of the user $U_n$ compared to the user $U_m$ as:

$$W_{U_n/U_m}^{Superiority} = \sum_{i=1}^{k} w_i \mid x_{ni} > x_{mi}$$  \hspace{1cm} (IV.1)

To evaluate the quality of our stable matching solution, we compute the following quality criteria as follows:
Let $pr_d(p)$ (resp. $pr_p(d)$) denote the position of passenger $p$ (resp. driver $d$) in the preference list of driver $d$ (resp. of passenger $p$). The regret cost $r(A)$ of a stable matching $A$ is defined as:

$$r(M) = \max_{(d,p) \in A} \max \{ pr_d(p), pr_p(d) \}$$  \hspace{1cm} (IV.2)

The egalitarian cost $c(M)$ is:

$$c(M) = \sum_{(d,p) \in A} pr_d(p) + \sum_{(d,p) \in A} pr_p(d)$$  \hspace{1cm} (IV.3)

The sex equality cost $d(M)$ is:

$$d(M) = \left| \sum_{(d,p) \in A} pr_d(p) - \sum_{(d,p) \in A} pr_p(d) \right|$$  \hspace{1cm} (IV.4)

Finally, to evaluate the impact of stability on system performance, we compare the value of the optimal objective function for unconstrained matching ($A$), i.e. relaxing constraint
Experimental Results

(12), and with that for stable matching ($A^*$). We define the price of stability $\delta$ as follows:

$$\delta = \frac{A - A^*}{A} \quad (IV.5)$$

3.3 Data sets

Since real world transport and social data sets are not available, in an attempt to evaluate the performance of the proposed approach, simulated data sets are derived and used. The source data utilized in testing are commercial products of Geomatic, a Danish company specializing in geo-demographic data and analysis for market segmentation, business intelligence, and direct marketing [66]. A few constraints are added so as to transfer them into multi preference instances.

Our data is stored in six tables DriverProfile Table, DriverPreferences Table, DriverWeight Table, PassengerProfile Table, PassengerPreferences Table and PassengerWeight Table.

**DriverProfile Table**

The DriverProfile table is described in Table **IV.1**

| Field          | Designation          | Type       |
|----------------|----------------------|------------|
| **ID**         | Unique identifier    | int(11)    |
| Name           | Full name            | varchar(50)|
| Gender         | Gender               | varchar(10)|
| BirthDate      | Date of birth        | date       |
| Status         | Marital status       | varchar(20)|
| PhoneNumber    | Phone number         | varchar(30)|
| Email          | E-mail address       | varchar(100)|
| VRange         | Vehicle range        | varchar(20)|
| Pets           | Pet friendliness     | varchar(10)|
| Music          | Listening to music   | varchar(10)|
| Smoking        | Smoking habit        | varchar(10)|
| SocialBehavior | Social behavior      | double     |
| DrivingSkills  | Driving skills       | double     |
| Reliability    | Reliability          | double     |

Table IV.1 – The DriverProfile table

**DriverPreferences Table**

The DriverPreferences table is described in Table **IV.2**
3 Experimental environment

Table IV.2 – The DriverPreferences table

| Field       | Designation          | Type         |
|-------------|----------------------|--------------|
| ID          | Unique identifier    | int(11)      |
| GenderPref  | Gender preference    | varchar(10) |
| AgePref     | Age preference       | int(3)       |
| AgeTolerance| Age tolerance        | int(3)       |
| StatusPref  | Marital status preference | varchar(20) |
| PetsPref    | Pets preference      | varchar(10) |
| MusicPref   | Music preference     | varchar(10) |
| SmokingPref | Smoking preference   | varchar(10) |

DriverWeight Table

The DriverWeight table is described in Table IV.3

| Field       | Designation          | Type         |
|-------------|----------------------|--------------|
| ID          | Unique identifier    | int(11)      |
| GenderWeight| Gender weight        | int(2)       |
| AgeWeight   | Age weight           | int(2)       |
| StatusWeight| Marital status weight| int(2)       |
| PetsWeight  | Pets weight          | int(2)       |
| MusicWeight | Music weight         | int(2)       |
| SmokingWeight| Smoking weight     | int(2)       |
| SocialBehaviorWeight | Social behavior weight | int(2) |
| ReliabilityWeight | Reliability weight | int(2) |

PassengerProfile Table

The PassengerProfile table is described in Table IV.4

PassengerPreferences Table

The PassengerPreferences table is described in Table IV.5

PassengerWeight Table

The PassengerWeight table is described in Table IV.6
4 Experiments

4.1 Multi-criteria ranking

This section contains indicative results that derive from the utilization of the second component of SMRM to a simulated ridesharing infrastructure environment. Some indicative, realistic everyday scenarios are presented. Our Multi-criteria ranking component is compared against the Weighted Sum Model WSM used in [27] which can lead to comprehensive results and thus showcases the efficiency of our proposed solution. Three scenarios
will be presented. The scenarios are passenger-driven, in that they are differentiated based on passenger preferences and drivers profiles. In this respect, the first one presents a typical passenger service request. The second scenario presents a case where only one driver satisfies a high priority passenger preference. Finally, the third one serves as an example for the case when a passenger values extremely high a certain parameter (the vehicle range, in our case). We apply separately the two methods TOPSIS and WSM to rank drivers and we compare their respective results. To do so, we compute the respective $C^*$ and $A_{WSM-score}$ (as presented in formula IV.6) values for every candidate driver. Through ranking these values, we obtain two different preference lists of the passenger.

$$A_{WSM-score}^i = \sum_{j=1}^{n} w_j a_{ij}, \text{ for } i = 1, ..., m$$  

(IV.6)

4.1.1 Scenario 1: Regular ridesharing service request

We consider a passenger $P1$ who has already registered on the SMRM and therefore disposes a unique identity in the system. He is supposed to have already filled his personal profile, stating his personal preferences on the driver and also depicting the weights of parameters. Fig.IV.2 presents the preferences and their respective weights.

At the same time, six (6) drivers make a ridesharing system request, making the system aware that they fulfill the spatio-temporal constraints of the passenger $P1$. Fig.IV.3 presents the drivers profiles.

In the sequel, the two methods TOPSIS and WSM are separately responsible for eval-

---

### Table IV.6 – The PassengerWeight table

| Field                      | Designation            | Type    |
|---------------------------|------------------------|---------|
| **ID**                    | Unique identifier      | int(11) |
| GenderWeight              | Gender weight          | int(2)  |
| AgeWeight                 | Age weight             | int(2)  |
| StatusWeight              | Marital status weight  | int(2)  |
| VHRangeWeight             | Vehicle range weight   | int(2)  |
| PetsWeight                | Pets weight            | int(2)  |
| MusicWeight               | Music weight           | int(2)  |
| SmokingWeight             | Smoking weight         | int(2)  |
| SocialBehaviorWeight      | Social behavior weight | int(2)  |
| DrivingSkillsWeight       | Driving skills weight  | int(2)  |
| ReliabilityWeight         | Reliability weight     | int(2)  |
Evaluating simultaneously the multiple constraints and ranking possible matches for the passenger $P_1$ according to his preferences. Specifically, taking into consideration the data provided in figure IV.2 and figure IV.3, the judgment matrix of $P_1$ presented in figure IV.4 is formed.

Thereafter, for every candidate driver, we calculate his respective $C^*$ and SM values,
based on the Judgment matrix and the passenger weights, as presented in Fig. IV.5. Through ranking these values, we obtain two different preference lists of the passenger P1.

![Figure IV.5 – Scenario 1- The result](image)

Based on the results, the preference list obtained by TOPSIS method is $PL_{TOPSIS}(P1) = D4 – D5 – D6 – D2 – D3 – D1$ and that obtained by the WS model is $PL_{WSM}(P1) = D6 – D5 – D4 – D2 – D3 – D1$. By the TOPSIS method, the first place is occupied by D4 as D4’s $C^*$ value is the highest, whereas it is occupied by D6 by the WS model as D6’s $A_{WSM-score}$ value is the highest. Observing these two drivers, we find that D4 complies with P1’s preferences regarding gender, vhrange and smoking. In contrast, D6 does not meet any of these preferences. In addition, D4 exceeds D6 on the age and the social behavior preferences. All of these preferences have a total weight of 31. On the other hand, D6 exceeds D4 only on the driving skills and the reliability preferences that have a total weight of 15.

4.1.2 Scenario 2: Single driver for a high priority preference

In this case, we consider the same passenger P1 with the same preferences and the same weights as shown in Fig. IV.2. On the other hand, six (6) other drivers wish to make the same itinerary as P1 and seem to be close in time. Out of the 6 drivers, only one meets the preference of the gender that P1 considers with driving skills as more important factors to make the match. Fig. IV.6 presents the drivers profile.

As explained in scenario 1, taking into consideration the data provided in Fig. IV.2 and Fig. IV.6, the judgment matrix of P1 presented in Fig. IV.7 is formed. Then, based on the judgment matrix and the weights, we obtain the result shown in Fig. IV.8.

As expressed in the figure above, the preference list obtained by TOPSIS method is
Experimental Results

Figure IV.6 – Scenario 2- The drivers profiles

| Driver_ID | Gender | Age  | Status | VRange | Pets | Music | Smoking | Social Behavior | Driving Skills | Reliability |
|-----------|--------|------|--------|--------|------|-------|---------|----------------|---------------|-------------|
| D1        | 1      | 0.23 | 1      | 1      | 0    | 0     | 1       | 9.17           | 7.7           | 1.47        |
| D2        | 0      | 0.33 | 0      | 1      | 1    | 1     | 0       | 7.85           | 0.95          | 0.35        |
| D3        | 0      | 0.21 | 1      | 1      | 0    | 1     | 1       | 9.32           | 4.92          | 8.05        |
| D4        | 0      | 0.25 | 0      | 1      | 1    | 1     | 0       | 9.15           | 1.44          | 9.77        |
| D5        | 0      | 0.67 | 0      | 0      | 1    | 0     | 1       | 7.52           | 7.33          | 9.84        |

Figure IV.7 – Scenario 2- P1 judgment matrix

| Driver_ID | Gender | Age  | Status | VRange | Pets | Music | Smoking | Social Behavior | Driving Skills | Reliability |
|-----------|--------|------|--------|--------|------|-------|---------|----------------|---------------|-------------|
| D1        | 1      | 0.23 | 1      | 1      | 0    | 0     | 1       | 9.17           | 7.7           | 1.47        |
| D2        | 0      | 0.33 | 0      | 1      | 1    | 1     | 0       | 7.85           | 0.95          | 0.35        |
| D3        | 0      | 0.21 | 1      | 1      | 0    | 1     | 1       | 9.32           | 4.92          | 8.05        |
| D4        | 0      | 0.25 | 0      | 1      | 1    | 1     | 0       | 9.15           | 1.44          | 9.77        |
| D5        | 0      | 0.67 | 0      | 0      | 1    | 0     | 1       | 7.52           | 7.33          | 9.84        |

Figure IV.8 – Scenario 2- The result

\[ PL_{TOPSIS}(P1) = D1 - D4 - D6 - D3 - D5 - D2 \] and that obtained by the WS model is 
\[ PL_{WSM}(P1) = D6 - D4 - D1 - D3 - D5 - D2. \] TOPSIS method decides in favor of \( P1 \) and \( D1 \), as \( D1 \)'s \( C^* \) value is the highest, among the six candidate drivers. However, \( D1 \) occupies the third place and \( D6 \) the first place with the WS model. It is clear that \( D1 \) is the most appropriate match for \( P1 \), meeting him only the gender preference. It may also be observed that beside the satisfaction of the gender preference, \( D1 \) has better values than \( D6 \) in terms of social behavior and driving skills preferences. Furthermore, unlike \( D6 \), \( D1 \) fulfills the Status and the vhrange constraints. Therefore, \( D1 \) surpasses \( D6 \) with
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a total weight equal to 33 (9 + 1 + 6 + 7 + 10).

4.1.3 Scenario 3: An extremely high preference

In this case, stating the weight of Vhrange to 10, passenger \( P_2 \) wishes to be matched to a driver with a comfortable car. Figure IV.9 describes \( P_2 \)'s preferences and their respective weights. We consider that the same six drivers of scene 1 (with profiles presented in Fig.IV.3) fulfill also the spatio-temporal constraints of \( P_2 \).

![Figure IV.9](image)

Figure IV.9 – Scenario 3- The preferences and weights vectors of passenger P2

Following the examples of the previous scenarios, we compute the judgment matrix of \( P_2 \) (presented in Fig.IV.10). Then, based on the judgment matrix and the weights of \( P_2 \), we obtain the result shown in Fig.IV.11. According to the results obtained in the

![Figure IV.10](image)

Figure IV.10 – Scenario 3- P2 judgment matrix

P2, we obtain the result shown in Fig.IV.11.
Experimental Results

Figure IV.11 – Scenario 3- The result

The figure above, TOPSIS method produces $P_{L_{TOPSIS}}(P2) = D4 - D3 - D6 - D5 - D2 - D1$ whereas WS model produces $P_{L_{WSM}}(P2) = D6 - D5 - D4 - D2 - D3 - D1$ as a preference list of $P2$. As it may be observed, the passenger thinks of the vehicle range as a very important factor of the trip. Another point to underline is that only Drivers $D3$ and $D4$ meet this constraint. These last two drivers occupy the first places of the $P2$’s preference list according to the TOPSIS method. However they occupy the third and the fifth place according to WS model. We also note that, beside selecting the most appropriate drivers regarding the highest preference, the head of the TOPSIS list ($D4$) transcends the head of the WSM list ($D6$) with a total weight equal to 18 ($3 + 10 + 5$).

In concluding, we manifest that our approach selects the most appropriate candidates with respect to the passenger preferences. In the first scenario, the head of the TOPSIS list exceeds that of the WS model on preferences with a total Weight Superiority ($W_{D4/D6}^{Superiority}$) equal to 31. However, the head of the WS model list exceeds that of the TOPSIS on preferences with a Weight Superiority ($W_{D6/D4}^{Superiority}$) of 15. In the second scenario, the first with TOPSIS surpasses that with WS with a Weight Superiority ($W_{D1/D6}^{Superiority}$) equal to 33. The latter only overtakes the top of the TOPSIS list on preferences with a Weight Superiority ($W_{D6/D1}^{Superiority}$) of 8. Finally, the same result is obtained in the third scenario. Indeed, the top of the TOPSIS list exceeds the top of the WS list with a Weight Superiority ($W_{D4/D6}^{Superiority}$) equal to 18. On the other hand, the top of the WSM list exceeds the top of the TOPSIS list with a Weight Superiority ($W_{D6/D4}^{Superiority}$) equal to 12. Fig IV.12 graphically presents the Weight Superiority obtained by the heads of the lists of the two methods in the three scenarios.
4.2 Stable matching

This section contains indicative results that derive from the utilization of the third component of SMRM to a simulated ridesharing infrastructure environment.

4.2.1 Test scenarios

We choose to compare our Stable Matching SM component in terms of the previously presented metrics against the classical Gale-Shapley GS algorithm since only the approach presented in [62] integrated the problem of stable marriage. The latter relied on the GS algorithm and assumed that the number of passengers was equal to that of drivers. For this reason, we used a data set with equal sets of passengers and drivers. On the other hand, we used unequal sets data source to show the performance of our system without comparing its performance to that of GS algorithm since the latter does not support unequal sets. We use data sizes of up to 1,000, while we generate synthetic data of diverse skewness and types. In our experiments, the egalitarian cost and sex equality cost metrics are normalized, i.e. divided by $n$. 

![Weight Superiority](image)
Figure IV.13 – Regret cost of stable matching within equal sets

Figure IV.14 – Egalitarian cost of stable matching within equal sets
4 Experiments

Figure IV.15 – Sex equality cost of stable matching within equal sets

Figure IV.16 – Price of stability within equal sets
4.2.2 Results

Fig. IV.13, Fig. IV.14 and Fig. IV.15 show the evolution of the regret cost, the egalitarian cost and the sex equality cost of our algorithm compared to the GaleShapley algorithm w.r.t. the number of users in the system. We observe that the regret cost and the egalitarian cost of both algorithms increase as far as the number of users in the system increases. However, we note that the sex equality cost is independent of the users’ number. This is explained by the fact that assigning equal importance to the preferences of passengers and drivers is not influenced by the number of users.

In addition, Fig. IV.13, Fig. IV.14 and Fig. IV.15 demonstrate that the two algorithms follow the same behavior within the three metrics. However, we note that GS achieves in many cases far worse quality in all metrics. Indeed, SM performs 5% better than GS in terms of regret cost and egalitarian cost. Consequently, in SM algorithm the preferences of every individual are more considered to be equally important, i.e. it minimizes better the difference in happiness of all the passengers and the drivers. Similarly, we see in Fig. IV.15 that SM algorithm achieves a superior performance of 20% in terms of sex equality cost, which indicates that, in our solution, the drivers are as pleased with the matching as the passengers.
Figure IV.18 – Variation of the price of stability within unequal sets
Experimental Results

Since we model a ridesharing provider that tries to achieve a right stable outcome, studying the effect of enforcing stability is worth of interest. Fig. IV.16 investigates how large the price of stability might be when using the two different algorithms \( SM \) and \( GS \). As expected, we remark that the price of stability is independent of the users’ number and it is relatively significant and represents a 10% approximate reduction of the objective value with \( SM \) algorithm. Nevertheless, the costs of enforcing stability are significantly higher in \( GS \) with a worse price of stability of 22% compared to \( SM \).

Studying the impact of the number of users on the execution time of the different algorithms is of paramount importance. Indeed, Fig. IV.17 shows that the execution time of the three algorithms varies substantially according to the users’ number. \( SM \) runs in approximately the same time as \( GS \), whereas the latter slightly outperforms \( SM \) in some cases. This is owing to the fact that within the \( SM \) algorithm, additional tests are performed in order to check the set sizes.

To assess the performance of our system in an unequal set case, we present the price of stability in different data sizes. In Fig. IV.18(a) we vary the number of passengers from 5 to 1000 while fixing the number of drivers to 500. In Fig. IV.18(b) we vary the number of drivers from 5 to 1000 while fixing the number of passengers to 500. The figures demonstrate that enforcing equal datasets comes at the cost of deteriorating the system-wide solution quality. Indeed, the price of stability is relatively small and represents a 3% approximate reduction in the objective value, however as expected, it reaches a peak when the size of drivers is equal to that of passengers. This is explained by the originality and efficiency of the \( SM \) algorithm, for unequal sets, which finds the optimal stable solution for the smaller set. In fact, \( SM \) operates such that we obtain the smaller set’s optimal solution. Thus, if there are fewer drivers than passengers, the drivers’ optimal solution is reached. Nevertheless, if there are more drivers than passengers, the passengers’ optimal solution is obtained. This stable solution is close to the unconstrained optimal solution.

5 Conclusion

The solution we propose is particularly well suited to our purpose. It is in this context that the main lines of this chapter are written. Indeed, to make the theoretical performances coincide with the practical performances, we took good care to make the appropriate technical, technological and architectural choices and that would not inter-
5 Conclusion

fere with our projects of optimization of the quality of service. According to our strategic and methodological choices of analysis, design, modeling and specification of our system, we have brought into play the concepts of operational research, artificial intelligence and sustainable development. An extensive experimental evaluation has shown that SMRM performs better than its competitor in terms of multi-criteria evaluation, stability quality and stability cost. The results have also demonstrated the efficiency of our solution, for unequal sets, which finds the optimal stable solution for the smaller set.
Conclusion

The car occupies an important place in the individuals’ life and remains always a source of very important and essential mobility. This does not preclude the fact that it has several disadvantages from several points of view (financial, environmental, societal, etc.).

In order to meet the needs of innovation while remaining in a respectful framework of fundamental environmental conditions for a healthy climate, ridesharing is presented as the key solution for a development without harmful consequences in addition to being of very advantageous economic order.

Based on an elaborate study of this concept, we have outlined the main lines of our proposal based on the limitations of existing works. We plan then through this master to remedy the absence of personal constraints and stability of matching aspects that make great weakness of the existing systems. Our interests, being among others of a practical nature, aim at making available to the general public, particular users or researchers an operational and friendly system. But also a system that promises the satisfaction of drivers and passengers’ social preferences, considering the notion of stability for rideshare matches.

We focused our efforts on the implementation of an effective strategy of resolution taking advantage of a mixture of concepts; namely the MCDMs and the SMP. An alliance of these two fundamentally rich concepts was the main contribution of our SMRM system.

We broke SMRM into three main components: Preference Satisfier, Multi-Criteria Ranking, and Stable Matching. The Preference Satisfier component computes a judgment matrix for each user based on their preferences and weights as well as on the profile and received evaluations of each correspondent. Then, the Multi-Criteria Ranking component is based on TOPSIS method as correspondents ranking tool to evaluate the multiple constraints simultaneously. Finally, the stable matching component relies on the approach
of stable marriage and returns the stable matching where there is no pair of participants
that both prefer each other to the partners that they are matched to.

An extensive experimental evaluation has shown that SMRM selects the most appropriate
candidates with respect to the passenger preferences. In addition, we manifest that
the stable matching component performs better than its competitor in terms of stabil-
ity quality and stability cost. The results have also demonstrated the efficiency of our
solution, for unequal sets, which finds the optimal stable solution for the smaller set.

As future work, we aim to develop machine learning techniques that could create col-
lective knowledge on user preferences, which will be exploited by SMRM in making the
convenient recommendations. Indeed, with the prevalence of GPS-enabled devices, the
exponentially growing popularity of social networking and the voluntary sharing of per-
sonal information online, we not only learn about the users’ life experiences but also about
their life modes. Ridesharing recommendations from online data can be seen as a kind of
personal optimizing service, which may help to improve users experience on ridesharing.

Additionally, in our approach, we considered the situation, in which drivers and pas-
sengers fulfill spatio-temporal constraints. This work could be extended on developing a
spatio-temporal matching model using a skyline method. Thereby, the Skyline query is
used to find a set of non-dominated correspondents by filtering the interesting matches
of a potentially large dataset based on origin, destination, and time constraints. With a
growing number of users involving multi-constraints, skyline queries can be used to answer
this problem accurately and efficiently.
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