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ICAI

Master’s Degree in Industrial Engineering

Master Thesis

Latent Demand Reduction For Carsharing Companies in Madrid

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Madrid

July 2022

Declaro, bajo mi responsabilidad, que el Proyecto presentado con el título

LATENT DEMAND REDUCTION FOR CARSHARING COMPANIES IN MADRID

en la ETS de Ingeniería - ICAI de la Universidad Pontificia Comillas en el

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Autorizada la entrega del proyecto

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REDUCCIÓN DE LA DEMANDA LATENTE DEL CARSHARING EN MADRID

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RESUMEN DEL PROYECTO

1. Introducción

a. Planteamiento del problema

Debido al aumento de la población en las ciudades urbanas y al futuro desarrollo de las ciudades 4.0, resulta necesario y esencial mejorar la calidad de la movilidad urbana. Una forma de conseguir esto es implementando el *carsharing* como uno de los principales medios de transporte de personas en las ciudades. Es por ello por lo que es necesario promover dicho sistema de movilidad inteligente, pues como se ha explicado anteriormente, la implementación del *carsharing* conlleva grandes ventajas y repercusiones que favorecen al desarrollo de las ciudades sostenibles.

Si bien es cierto que la pandemia sufrida en los últimos años ha tenido un gran impacto económico en todos los ámbitos y aspectos, cabe recalcar que ha favorecido al desarrollo de una mentalidad más sostenible. Asimismo, en lugar de escoger las trayectorias más rápidas para llegar a un determinado punto, la sociedad prefiere decantarse por el trayecto más seguro posible. Por ello, con la reactivación de la movilidad urbana, se busca una movilidad urbana tanto segura como sostenible (El ‘carsharing’ como pieza clave en la movilidad post-Covid, 2022). El *carsharing* será capaz de satisfacer estas necesidades, pues es reconocido como el medio de transporte que más promueve la transición hacia una movilidad eléctrica en las ciudades.

Ahora bien, con el fin de maximizar el bienestar social y reducir las emisiones de CO_2, es de vital importancia que la sociedad emplee los vehículos de movilidad compartida como medio de transporte. Pero, para poder impulsar

adecuadamente dicho servicio, será necesario reducir hasta eliminar los efectos adversos de la movilidad compartida, como lo es la demanda latente.

Por ello, la principal motivación de este trabajo es reducir dicha demanda a partir de la implementación de un modelo que busque maximizar el beneficio de las empresas de *carsharing*, a la vez que se consiga aumentar el bienestar tanto social como medioambiental. Mediante la reducción de la demanda latente por parte de las empresas de *carsharing*, cada vez más individuos se decantarán por escoger este tipo de medio de transporte. No solo porque es cómodo y flexible, sino también porque supone un gran ahorro económico. De esta forma se favorecerá al desarrollo de las ciudades 4.0 y supondrá un nuevo paradigma para nuestra sociedad.

b. Objeto del proyecto

Cabe destacar que el objetivo principal del proyecto será analizar el impacto de la reserva de plazas de aparcamiento por parte de las empresas de *carsharing* en la demanda latente de este servicio de movilidad. El estudio de caso se realizará sobre la ciudad de Madrid, utilizando datos de urbanismo y movilidad. De este modo, se ajustará un modelo para optimizar tanto el número de plazas necesarias como su ubicación. Entre los objetivos del proyecto a destacar se encuentran:

- Elegir el mejor subconjunto de plazas de aparcamiento para que las empresas de *carsharing* las alquilen.
- Obtener una distribución territorial justa de las plazas de aparcamiento que satisfaga las necesidades de la población.
- Encontrar un equilibrio óptimo entre los intereses de la población y los de las empresas con ánimo de lucro.
- Proporcionar una herramienta matemática de fácil uso para los gobiernos locales que pueda adoptarse y ajustarse fácilmente.

Para resolver de la mejor manera posible el problema al que se enfrentan los gobiernos de todo el mundo, se aplicará un modelo matemático de optimización. El objetivo es obtener el mejor subconjunto de plazas de aparcamiento que mejor satisfaga la demanda latente, analizando y reduciendo la diferencia entre la demanda potencial y la satisfecha de las empresas de *carsharing*. Para conseguir esto último, este estudio se basará en los datos reales de alquiler de los operadores de *carsharing*. Por ello, el informe realizado por Gallardo et al. (2021) será una importante fuente de información.

Además, la metodología se ha codificado utilizando el lenguaje de programación Python, y se ha propuesto un algoritmo genético como solución al problema. Por tanto, este problema matemático tendrá como variables de decisión tanto la decisión de alquilar o no una plaza de aparcamiento como el número de plazas por aparcamiento.

2. Metodología

El modelo se ha implantado en la ciudad de Madrid debido a que, al ser un importante centro financiero, Madrid se ha convertido en una ciudad de tránsito, lo que significa que la movilidad en la ciudad ha aumentado considerablemente. Un estudio realizado por Parkimeter revela que el tiempo medio de aparcamiento de los madrileños es de 95h y puede llegar a un total de 125h/año, siendo el Distrito Centro la zona donde es más difícil aparcar. (El 'carsharing' como pieza clave en la movilidad post-Covid, 2022). Esto último, junto con el plan de calidad del aire 'Madrid 360' (Madrid 360 * Madrid 360, 2022), ha provocado una situación en la que es necesario reorganizar y actualizar los sistemas de transporte, para que Madrid pueda convertirse en una de las ciudades punteras en cuanto a la transición inteligente.

Como se ha dicho anteriormente, este informe pretende aumentar el uso del *carsharing* como medio de transporte principal. Para ello, se aplicará un modelo de optimización matemática que se explicará a continuación

a. Configuración del modelo

En primer lugar, el área de estudio se discretizará en celdas rectangulares, creando una cuadrícula que estará compuesta por 17 filas y 19 columnas. La Figura 1 muestra cómo se va a implementar esto último:

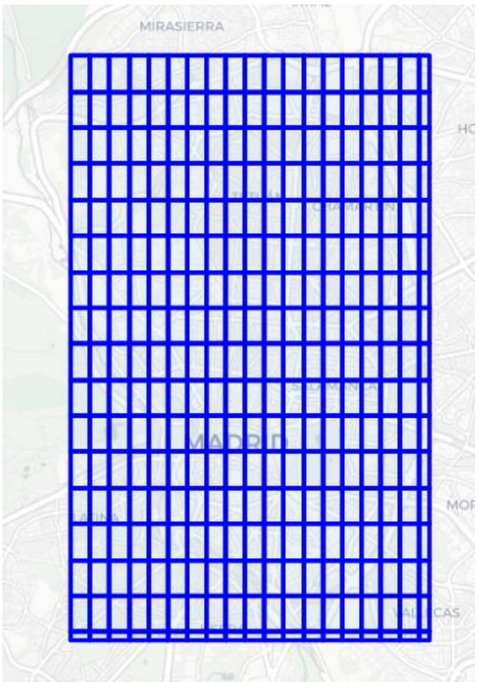

Fig. 1 – Discretización de la zona a estudiar

Recuperando los datos de la página web de Madrid (2022), se ha podido obtener la ubicación exacta de las estaciones de aparcamiento público de la ciudad. La figura 2 muestra la localización de dichos parkings en la correspondiente zona discretizada.

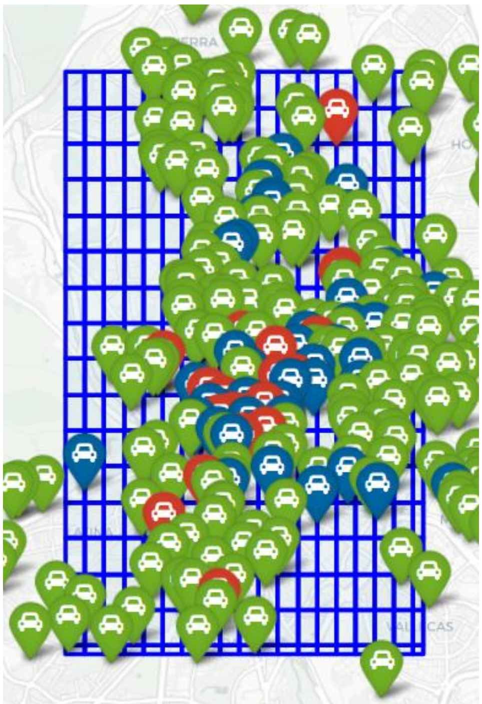

Fig. 2 – Parkings públicos en Madrid

b. Algoritmo

El algoritmo que se va a implementar se trata de un algoritmo genético. Este algoritmo heurístico está optimizando constantemente el problema a resolver, obteniendo así la mejor solución posible.

i. Función objetivo

La función a aplicar será la siguiente:

$$maxD = \sum_{x=1}^{m}\sum_{y=1}^{n} \min A = \sum_{x=1}^{m}\sum_{y=1}^{n} \frac{(A_{ORIGIN} + A_{DESTINATION})}{2} \tag{1}$$

Siendo A_{ORIGIN} el número total de viajes latentes que se originan en una cuadrícula determinada, y $A_{DESTINATION}$ el número total de viajes latentes que terminan en una cuadrícula determinada de la malla.

ii. Restricciones

Las funciones de penalización que se van a aplicar serán las siguientes:

- Tarifa de parking
- Número máximo y mínimo de parkings:
- Número máximo de plazas de aparcamiento en toda la ciudad:

3. Resultados

Una vez implementado el modelo matemático, se realizaron un total de 10 iteraciones para verificar la viabilidad del modelo.

En definitiva, se han elegido un total de 19 parkings en la ciudad de Madrid. En la siguiente figura se muestra la distribución de los parkings públicos elegidos y el número de plazas que deberían asignarse en cada uno de ellos. Esta figura se ha presentado junto con la distribución latente global presente en Madrid:

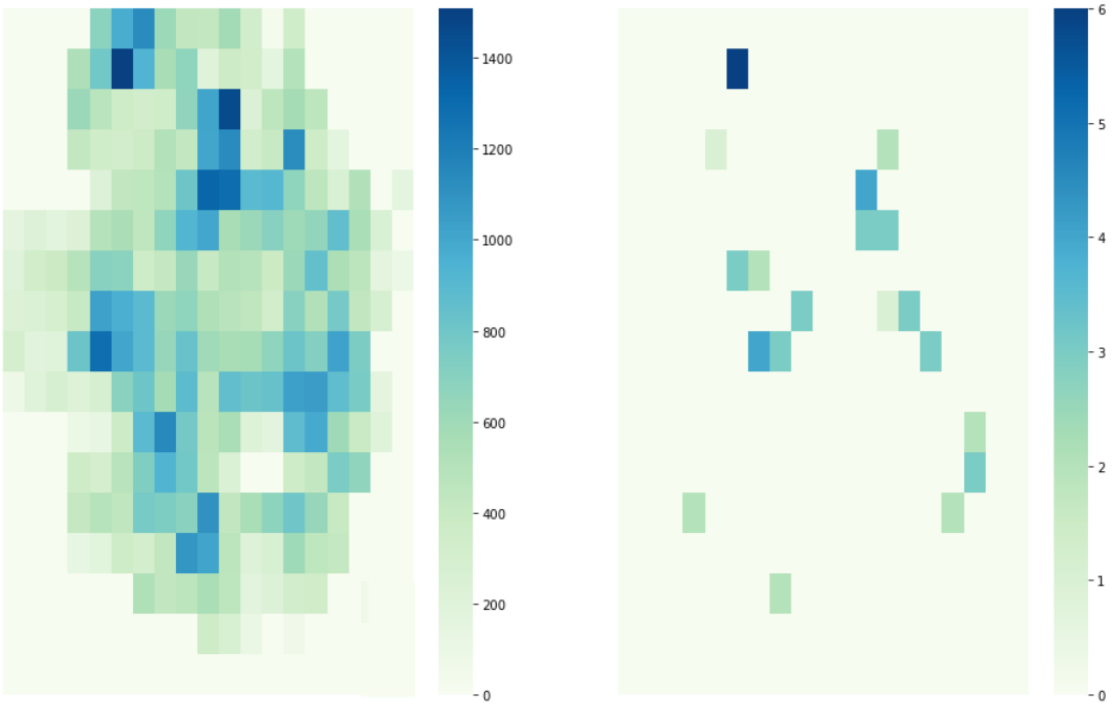

Fig. 3 – Distribución de los parkings en Madrid

En definitiva, los parkings mostrados en la figura se corresponden con los siguientes:

- Parking Sarriá (residentes): 6 plazas
- Parking Aguilar de Campoo (residentes): 1 plaza
- Parking Hurtado Mendoza (residentes): 2 plazas
- Parking Panamá (residentes): 4 plazas
- Parking San Juan de la Salle (residentes): 3 plazas
- Parking Santo Domingo de Silos (residentes): 3 plazas
- Parking Doménico Scarlatti (residentes): 3 plazas
- Parking San Francisco de Sales I (residentes): 2 plazas
- Parking Bravo Murillo (residentes): 3 plazas
- Parking Lagasca (residentes): 1 plaza
- Parking Castelló (residentes): 3 plazas
- Parking Ortega y Gasset (residentes): 3 plazas
- Parking Conde del Valle de Súchil (residentes): 3 plazas
- Parking Galileo (residentes): 3 plazas
- Parking Sainz de Baranda (residentes): 2 plazas
- Parking Estrella Polar (residentes): 3 plazas
- Parking Conde de Casal (residentes): 2 plazas
- Parking Iván de Vargas (residentes): 2 plazas
- Parking Pedro Yagüe (residentes): 2 plazas

Para evaluar el impacto de este proyecto, se ha realizado un breve estudio económico. Aquí se ha evaluado el ahorro de capital de una empresa de *carsharing* que ya no debe mover parte de su flota de vehículos con el fin de aumentar la disponibilidad. Para ello, es imprescindible considerar el número de plazas de aparcamiento que se distribuirán alrededor de la ciudad de Madrid. Con ello, en este estudio se colocarán un total de 50 plazas de aparcamiento en las diferentes estaciones de aparcamiento de Madrid.

A la hora de evaluar el impacto económico, se tendrán en cuenta únicamente a los empleados responsables de la distribución de los coches. Esto último se debe a que se requerirá un menor número de empleados para trasladar los vehículos de *carsharing* con el fin de aumentar su disponibilidad en la ciudad (Cordeiro, 2018), ya que habrá coches disponibles en las posibles estaciones de estacionamiento que se hayan elegido.

Además, se considerará una reducción total del 7% en los empleados. Según el informe de Codeiro (2018), los costes personales por vehículo de *carsharing* ascienden a un total de 24,66€/día. Considerando que este estudio tiene en cuenta una jornada laboral completa, las empresas de *carsharing* estarán ahorrando un total de 1,73*50= 86,5€/día. Lo que debe quedar claro es que no se ha tenido en cuenta el aumento de la demanda por día, lo que significa que los beneficios de los vehículos de *carsharing* aumentarán considerablemente tras la aplicación de esta metodología.

Como último paso, se ha realizado un análisis de sensibilidad. En este análisis se han realizado dos casos de estudio. En el primero se incrementa el número de plazas de aparcamiento de 50 a 60, teniendo en cuenta un máximo de 40 estaciones de aparcamiento; mientras que en el segundo se consideran 250 plazas de aparcamiento y un máximo de 50 estaciones de aparcamiento. Los resultados muestran que, aunque se incrementa el número de estaciones, el mejor individuo tiene sólo 25 parkings, y asigna las 250 plazas entre dichos aparcamientos, lo que significa que cada estación de aparcamiento tiene demasiadas plazas reservadas para las empresas de *carsharing*, y esta situación no es deseada. Además, el primer caso de estudio tiene un mejor valor de fitness. Por lo tanto, la solución no es incrementar el número de estaciones de aparcamiento, sino optimizar este valor.

4. Conclusiones

Cabe destacar que los resultados obtenidos en este proyecto indican que las zonas en donde se deberían asignar más plazas de aparcamiento se corresponden con: el eje norte de la Castellana, el barrio del Pilar y el barrio de Chamberí. Esto último coincide con los resultados obtenidos en el estudio realizado por Gallardo et al. (2021). Por tanto, si se colocasen plazas de aparcamiento destinadas al uso exclusivo del *carsharing* en dichos aparcamientos, la demanda latente podría reducirse considerablemente.

Asimismo, si este modelo se implantara en la ciudad de Madrid, habría que definir adecuadamente los datos de entrada para asegurar su correcta implementación y validez. Cabe mencionar que el modelo ha escogido parkings de tipo "residentes". Por ello, para poder implementar dicho estudio, será necesaria la cooperación del Ayuntamiento de Madrid.

Por lo tanto, aunque parece sencillo aplicar dicha solución, pueden surgir problemas legales con los residentes, ya que tendrán menos plazas disponibles para ellos en las estaciones de aparcamiento seleccionadas. Sin embargo, este estudio está fuera del alcance de este proyecto.

5. Referencias

(2022). Retrieved 2022, from https://www.peektraffic.eu/smart-mobility

Aparcamientos municipales - Aparcamientos públicos - Ayuntamiento de Madrid. (n.d.). Retrieved from Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Circulacion-y-aparcamiento/Aparcamientos-municipales?vgnextfmt=default&vgnextoid=38f87870f3c3b010VgnVCM100000d90ca8c0RCRD&vgnextchannel=b3128fb9458fe410VgnVCM1000000b205a0aRCRD&id

Cordeiro, A. B. (2018). Análisis de viabilidad económica y futuro del carsharing eléctrico en España.

Gallardo , A., Otero , Á., & Jiménez Octavio, J. R. (2021). Free-floating Car-sharing Demand Modeling for the Design of a Distributed Charging Infrastructure. Madrid Use-Case.

*Madrid 360 * Madrid 360*. (2022). Retrieved from Madrid 360: https://www.madrid360.es/

Servicio de Estacionamiento Regulado (SER). Residentes - Gestiones y Trámites. (2022). Retrieved from Sede.madrid.es: https://sede.madrid.es/portal/site/tramites/menuitem.62876cb64654a55e2dbd7003a8a409a0/?vgnextoid=3bbc52afa5ce6410VgnVCM1000000b205a0aRCRD&vgnextchannel=23f9a38813180210VgnVCM100000c90da8c0RCRD&vgnextfmt=default

Tarifas aparcamientos públicos de concesión municipal rotatorios y mixtos - Ayuntamiento de Madrid. (2022). Retrieved from Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Tarifas-aparcamientos-publicos-de-concesion-municipal-rotatorios-y-mixtos/?vgnextoid=2fa178875ee5e110VgnVCM2000000c205a0aRCRD&vgnextchannel=220e31d3b28fe410VgnVCM1000000b205a0aRCR

LATENT DEMAND REDUCTION FOR CARSHARING COMPANIES IN MADRID

1. Introduction

a. Problem Statement

Due to the increasing population in urban cities and the future development of Smart Cities, it is necessary and essential to improving the quality of urban mobility. One way to achieve this is by implementing carsharing as one of the main means of transport for people in cities. This is why it is necessary to promote such a smart mobility system because, as explained above, the implementation of carsharing has great advantages and repercussions that favour the development of sustainable cities.

While it is true that the pandemic of recent years has had a major economic impact on all areas and aspects, it is worth noting that it has helped to develop a more sustainable mindset. Also, instead of choosing the quickest routes to get to a certain point, society prefers to opt for the safest possible route. Therefore, with the revival of urban mobility, the aim is to achieve both safe and sustainable urban mobility (Carsharing as a key element in post-Covid mobility, 2022). Carsharing will be able to meet these needs, as it is recognised as the means of transport that most promotes the transition to electric mobility in cities.

However, in order to maximise social welfare and reduce CO_2 emissions, it is vital that society uses shared mobility vehicles as a means of transport. However, in order to properly promote this service, it will be necessary to reduce or even eliminate the adverse effects of shared mobility, such as latent demand.

Therefore, the main motivation of this work is to reduce this demand by implementing a model that seeks to maximise the profit of carsharing companies, while increasing both social and environmental welfare. By reducing latent demand from carsharing companies, more and more individuals will choose this mode of transport. Not only because it is convenient and flexible, but also because it saves money. In this way, the development of Smart Cities will be promoted and will represent a new paradigm for our society.

b. Goals and objectives

It is worth mentioning that the main objective of the project will be to analyse the impact of the reservation of parking spaces by carsharing companies on the latent demand for this mobility service. The case study will be carried out on the city of Madrid, using urban planning and mobility data. In this way, a model will be adjusted to optimise both the number of spaces required and their location. Among the objectives of the project to be highlighted, it is possible to find:

- To choose the best subset of parking spaces for carsharing companies to rent.
- To obtain a fair territorial distribution of parking spaces that meets the needs of the population.
- To find an optimal balance between the interests of the population and those of the for-profit companies.
- To provide a user-friendly mathematical tool for local governments that can be easily adopted and adjusted.

In order to best solve the problem governments all around the world are facing, a mathematical optimization model will be implemented. The objective is to obtain the best subset of parking slots that best satisfies latent demand, by analysing and reducing the difference between potential and satisfied demand from carsharing companies. To achieve the latter, this study will rely on real rental data from carsharing operators. Therefore, the report carried out by Gallardo et al. (2021) will be an important source of information.

What's most, the methodology was coded using Python programming language, and a metaheuristic algorithm was proposed as a solution to the problem. Therefore, this mathematical problem will have both the decision of whether to rent a parking slot or not and the number of slots per parking as decision variables.

2. Methodology

The model has been implemented in the city of Madrid, the most populated city in Spain. Without a doubt, Madrid is home not only to locals, but also to people from all over the world. Being an important financial centre, Madrid has become a city of transit, meaning that mobility in the city has increased considerably. A study carried out by Parkimeter reveals that the average parking time of Madrid's citizens is 95h and can reach a total of 125h/year, being the Centre District the most difficult one to park. (El 'carsharing' como pieza clave en la movilidad post-Covid, 2022). The latter, together with 'Madrid 360' air quality plan (Madrid 360 * Madrid 360, 2022), has caused a situation in which transport systems need to be reorganised and updated, so Madrid can become one of the top cities regarding the smart transition.

As it has been previously stated, this report aims to increase the use of carsharing as a principal means of transport through the implementation of a mathematical optimization problem. Without a doubt, the problem that is going to be tackled is a major problem for local governments. Thus, this project will provide a user-friendly mathematical tool for local governments that can be easily adopted and adjusted.

a. Model set-up

First of all, the area of study will be discretised into rectangular cells, creating a grid that will be composed of 17 rows and 19 columns. Figure 1 shows how the latter is going to be implemented:

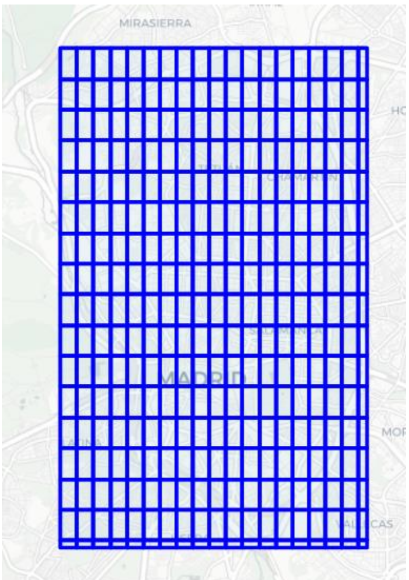

Fig. 1 – Discretization of the city of Madrid

Retrieving data from Madrid's web page (Aparcamientos municipales - Aparcamientos públicos - Ayuntamiento de Madrid, 2022), it has been possible to obtain the exact location of the public parking stations in the city. The following figure shows the location of these in relation to the discretized area.

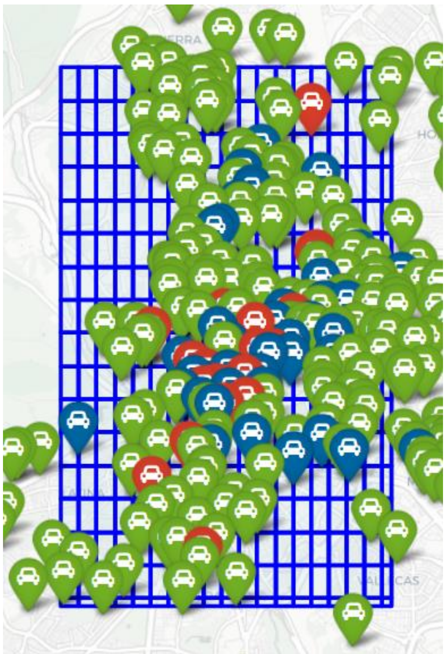

Fig. 2 - Location of public parking stations in Madrid

b. Algorithm

The algorithm that is going to be implemented is a genetic algorithm. This heuristic algorithm is constantly optimising the problem to be solved, thus obtaining the best possible solution.

i. Objective function

The objective function aims to maximise the demand following Equation:

$$maxD = \sum_{x=1}^{m}\sum_{y=1}^{n} \min A = \sum_{x=1}^{m}\sum_{y=1}^{n} \frac{(A_{ORIGIN} + A_{DESTINATION})}{2} \tag{1}$$

Being A_{ORIGIN} the total number of latent trips that are originated in a determined grid, and $A_{DESTINATION}$ the total number of latent trips that end in a determined grid of the mesh.

ii. Constraints

The penalty functions that are going to be applied:

- Parking fee
- Maximum and minimum number of parking stations
- Maximum number of parking slots in the entire city:

3. Results

Once the mathematical model has been implemented, a total of 10 iterations were conducted to verify the feasibility of the model.

All in all, a total of 19 parking stations in the city of Madrid were chosen. The following figure shows the distribution of the parking stations and the number of parking slots that should be allocated in each one of them. This figure has been presented together with the overall latent distribution present in Madrid:

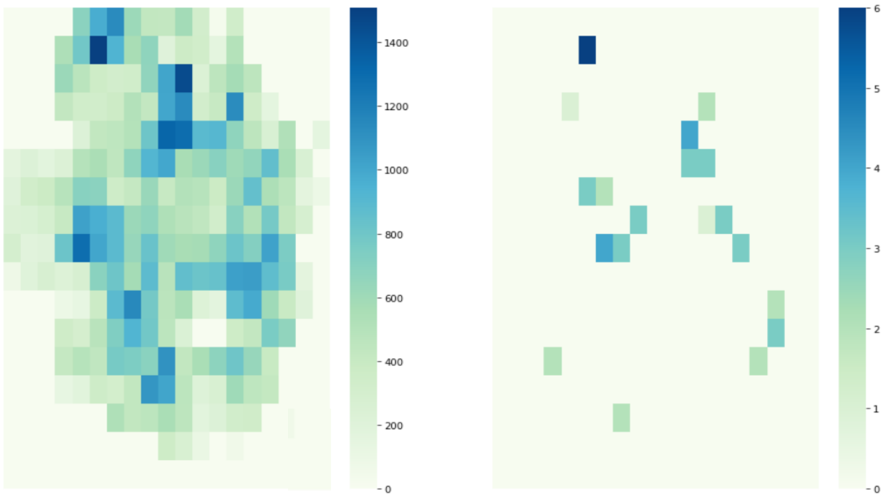

Fig. 3 – Parking slot allocation in Madrid

Therefore, the following parking stations will have reserved parking spaces for carsharing companies:

- Parking Sarriá (residents): 6 parking slots
- Parking Aguilar de Campoo (residents): 1 parking slot
- Parking Hurtado Mendoza (residents): 2 parking slots
- Parking Panamá (residents): 4 parking slots
- Parking San Juan de la Salle (residents): 3 parking slots
- Parking Santo Domingo de Silos (residents): 3 parking slots
- Parking Doménico Scarlatti (residents): 3 parking slots
- Parking San Francisco de Sales I (residents): 2 parking slots
- Parking Bravo Murillo (residents): 3 parking slots
- Parking Lagasca (residents): 1 parking slot
- Parking Castelló (residents): 3 parking slots
- Parking Ortega y Gasset (residents): 3 parking slots

- Parking Conde del Valle de Súchil (residents): 3 parking slots
- Parking Galileo (residents): 3 parking slots
- Parking Sainz de Baranda (residents): 2 parking slots
- Parking Estrella Polar (residents): 3 parking slots
- Parking Conde de Casal (residents): 2 parking slots
- Parking Iván de Vargas (residents): 2 parking slots
- Parking Pedro Yagüe (residents): 2 parking slots

In order to evaluate the impact of this project, a brief economical study has been conducted. Here, the capital savings from a carsharing company that no longer must move part of its fleet of carsharing vehicles to increase availability have been evaluated. Therefore, it is essential to consider the number of parking slots that will be allocated through the city of Madrid. During this study, a total number of 50 parking slots will be placed in the different parking stations in Madrid.

While evaluating the economic impact, employees that are responsible for the proper functioning of the service will be taken into consideration. The latter is due to the fact that fewer employees will be required to move the carsharing vehicles in order to increase their availability in the city (Cordeiro, 2018), since there will be available cars in the potential parking stations that have been chosen.

Moreover, a total of 7% of the total reduction of employees will be considered. Following Codeiro (2018), personal costs per carsharing vehicle amounts to a total of 24,66€/day. Considering this study takes a whole workday into account, carsharing companies will be saving a total of 1,73*50= 86,5€/day. What must be made clear is that the increase in demand per day has not been taken into consideration, meaning that the benefits of carsharing vehicles will increase considerably after the implementation of this methodology.

As a last step, a sensitivity analysis has been conducted. During this analysis, two study cases have been carried out. The first one increases the number of parking slots from 50 to 60, taking a maximum of 40 parking stations into consideration; whereas the second one considers 250 parking slots and a maximum of 50 parking stations. Results show that even though the number of stations gets incremented, the best individual has only 25 parking stations, and allocates the 250 slots between those ones, meaning that each parking station has too many parking spaces reserved for carsharing companies, and this situation is not desired. Moreover, the first case study has a better fitness value. Therefore, the solution is not to increment the number of parking stations, but to optimise this value.

4. Conclusions

Conclusions regarding results state that the areas where more parking slots should be allocated are: North of Castellana axis, barrio del Pilar, and Chamberí. The latter is in line with the results obtained in the study carried out by Gallardo et al. (2021). Therefore, it is possible to ensure that if there are more parking slots allocated in those parking stations, latent demand will be reduced considerably.

If this model was to be implemented in the city of Madrid, the data input should be properly defined in order to ensure its relevance and validity. Moreover, results show that parking stations that should be taken into consideration are of the type “residents”. Therefore, even though it seems straightforward to implement such solution, legal problems with residents may arise, since they will have fewer spots available to themselves in the selected parking stations. However, such a study is out of the scope of this project.

5. References

(2022). Retrieved 2022, from https://www.peektraffic.eu/smart-mobility

Aparcamientos municipales - Aparcamientos públicos - Ayuntamiento de Madrid. (n.d.). Retrieved from Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Circulacion-y-aparcamiento/Aparcamientos-municipales?vgnextfmt=default&vgnextoid=38f87870f3c3b010VgnVCM100000d90ca8c0RCRD&vgnextchannel=b3128fb9458fe410VgnVCM1000000b205a0aRCRD&id

Cordeiro, A. B. (2018). Análisis de viabilidad económica y futuro del carsharing eléctrico en España.

Gallardo , A., Otero , Á., & Jiménez Octavio, J. R. (2021). Free-floating Car-sharing Demand Modeling for the Design of a Distributed Charging Infrastructure. Madrid Use-Case.

*Madrid 360 * Madrid 360*. (2022). Retrieved from Madrid 360: https://www.madrid360.es/

Servicio de Estacionamiento Regulado (SER). Residentes - Gestiones y Trámites. (2022). Retrieved from Sede.madrid.es: https://sede.madrid.es/portal/site/tramites/menuitem.62876cb64654a55e2dbd7003a8a409a0/?vgnextoid=3bbc52afa5ce6410VgnVCM1000000b205a0aRCRD&vgnextchannel=23f9a38813180210VgnVCM100000c90da8c0RCRD&vgnextfmt=default

Tarifas aparcamientos públicos de concesión municipal rotatorios y mixtos - Ayuntamiento de Madrid. (2022). Retrieved from Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Tarifas-aparcamientos-publicos-de-concesion-municipal-rotatorios-y-mixtos/?vgnextoid=2fa178875ee5e110VgnVCM2000000c205a0aRCRD&vgnextchannel=220e31d3b28fe410VgnVCM1000000b205a0aRCR

MASTER

THESIS

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1. CHAPTER 1. INTRODUCTION

A phenomenon is currently unfolding that is gaining global significance: the Fourth Industrial Revolution (Industry 4.0). It is a technological revolution that impacts today's society, blending cutting-edge techniques with smart systems that integrate both organisations and people (2022). What's most, it alters how governments act in the face of global challenges, while relying on information and communication technologies (ICTs). It is worth mentioning that the emergence of this revolution is mainly due to the remarkable increase in population, as well as pollution and scarcity of resources. Therefore, cities have opted to develop a change of mentality and become sustainable cities: smart cities or cities 4.0 are here to stay (Iberdrola, 2022).

A key component in the development of smart cities is the intelligent mobility system, also known as Smart Mobility (Smart Mobility - Peek Traffic, 2022). Therefore, issues related to the accessibility of cities are becoming increasingly important. The aim is to optimise the flow of people in order to make it safer and more efficient, while at the same time reducing CO_2 emissions to improve air quality.

It is worth noting that in order to move towards a more sustainable future, it is necessary to rethink the use of existing transport systems. This is where carsharing services come into play since shared mobility could therefore be the future of transport. For those who have not heard this term before, carsharing is a mobility service whose main business model consists of renting a vehicle for short periods of time, and where the fee for such use is paid by the minute.

One of the great advantages of carsharing is that it has an extremely positive impact on the quality of urban life, thus reducing the adverse effects of current transport systems. The introduction of carsharing not only has an economic impact, as it reduces costs considerably compared to private car ownership but also has positive effects on the environment, as each carsharing vehicle replaces 9-12 private cars (Carrese, D'Andreagiovanni, Giacchetti, Nardin, & Zamberlan, 2021), thus reducing CO_2 emissions. It also leads to smoother traffic flow in the city, so that traffic is considerably reduced and parking in the city is no longer so complicated.

Despite having a wide range of advantages, the implementation of such shared mobility systems has not been an easy task, especially since it has been rejected by society at first. This is due to the fact that in a society where only private fast motorisation was of interest, the concept of carsharing (or shared mobility service) was hardly appealing (Carsharing: from present trend to future solution, 2022). However, after thorough research, it has become clear that the benefits of carsharing outweigh the disadvantages. As a result, there is a growing trend towards the implementation of this type of transport in cities.

However, such a system is imperfect and, although the fleet of vehicles of carsharing companies is distributed in the cities, it is still not able to satisfy all the existing demand. In fact, latent demand is one of the main factors that prevent people from choosing to use carsharing vehicles instead of other means of transport. It is worth mentioning that latent demand is the demand obtained by subtracting satisfied demand from potential demand. On the other hand, latent demand can also be defined as the demand of users who, despite the fact that carsharing would be very useful for them, do not use it due to a lack of knowledge, resources and/or information. In this way, latent demand could be defined as the demand that carsharing companies are not reaching.

Unfortunately, such demand will always exist, as it is very difficult to eliminate. Therefore, it is interesting to explore ways in which this latent demand can be reduced so that the development of mobility as a service can be boosted. In this way, cities can become greener, and the development of a sustainable ecosystem can be promoted while increasing carsharing companies' benefits considerably.

1.1. PROJECT MOTIVATION

Nowadays, in the current fast-changing environment, the rate at which the population is increasing is, without a doubt, terrifying. The latter, together with the existing development of smart cities, leads to a situation in which governments should take actions that improve the quality of urban mobility, that enhance the development of smart cities.

While it is true that the pandemic of recent years has had a major economic impact on all areas and aspects, it is worth noting that it has helped to develop a more sustainable mindset. Also, instead of choosing the quickest routes to get to a certain point, society opts for the safest possible route. Therefore, with the revival of urban mobility, the aim is to achieve both safe and sustainable urban mobility (El 'carsharing' como pieza clave en la movilidad post-Covid, 2022).

Carsharing will be able to meet these needs, as it is recognised as a means of transport that can promote the transition to electric mobility in cities; and brings multiple, green benefits to the table, such as traffic emission reduction and traffic emission alleviation (Sai, Bi, & Chai, 2020). Therefore, to favour the development of sustainable cities, such a smart mobility system must be promoted.

Nevertheless, in order to both properly promote this service and maximise operator's benefits while reducing CO_2 emissions, it will be necessary to decrease the adverse effects of shared mobility, such as latent demand.

Therefore, the main motivation of this work is to reduce this demand by implementing a model that seeks to maximise the profit of carsharing companies, while increasing both social and environmental welfare. By reducing latent demand from carsharing companies, demand could be potentially boosted. Not only because carsharing is convenient and flexible, but also because it make customers save money. In this way, the development of Smart Cities will be promoted and will represent a new paradigm for our society.

This research will focus mainly on parking slot allocation, since a hypothesis has been built around the fact that renting parking spaces for carsharing operators in determined parking stations could contribute to reducing latent demand. In order to achieve this, the latter will be based on a mathematical model that will best decide which parking slots should be rented by carsharing companies. This methodology will not only take into account user demand, such as potential and satisfied demand, but will also decide the best optimal distribution of parking slots that will achieve the maximisation of the benefits gained by carsharing companies, as latent demand will be reduced after the correct implementation of such model.

The goal of this study is to promote the implementation of carsharing into de urban mobility system. Moreover, the city of Madrid will be presented as a case study, and the best distribution of rented parking slots will be presented as a result.

This paper will be organised following the subsequent distribution. Chapter 2 will present the state-of-the-art regarding carsharing companies and parking slot allocation. Moreover, genetic algorithms will be defined, as it is the approach that will be taken in order to obtain the best possible distribution of parkings in a city. Moving on to Chapter 3, the model employed will be thoroughly developed. The main objectives will be clearly stated, and data sources will be outlined. Furthermore, Chapter 4 will present the results and evaluate a sensitivity analysis, to end with an economic study that will evaluate the benefits obtained by carsharing companies. To sum up, Chapter 5 will present conclusions and possible future improvements. Appendix A presents the alignment of this project with SDGs.

2. CHAPTER 2. LITERATURE REVIEW

This Section will discuss the state-of-the art of the most important topics related to this project: the sharing economy applied to carsharing, demand forecasting regarding carsharing and genetic algorithms.

To start, a literature review on how the sharing economy has led to parking allocation in cities all over the world will be presented. Several examples of cites that have already implemented this approach will be outlined, not only to demonstrate that it is possible to execute such matter in a city like Madrid, but also to underline the importance of retracing cities into more sustainable and green ones.

It is essential to outline that the model that is going to be developed in this project focuses on maximising the demand of carsharing users, thus optimising revenue obtained by carsharing companies. Therefore, to reach such goal, genetic algorithms will be applied as the main approach. So that the reader can get a better insight of how the model works, a literature review will be presented, carefully explaining each step of the process so the basics of genetic algorithms are fully understood.

2.1. CARSHARING

With the rise of both environmental and societal issues such as pollution and poverty, an increasing trend towards sustainability became more and more popular within society: the sharing economy (SE), characterised by two core concepts: sharing and connection. Without losing ownership, private individuals were now able to lease (free or for a fee) their resources and/or services in order to fully exploit the assets' potential (Rojanakit, Torres de Oliveira, & Dulleck, 2022). Without a doubt, the SE has brought several benefits to society, both financial and non-financial, not only because there is greater accessibility to resources in latent stages, but also because there is a greater connection between people.

The SE, first introduced in 1995 by eBay with the creation of the first online marketplace (The History of the Sharing Economy, 2022), has redefined the way society acts when using resources. What's most, it has become a new economic model that has changed the way several sectors, such as the transportation sector, function (Survival strategies of the sharing economy from the pandemic to a new normal: A dynamic capabilities approach, 2022). Regarding the latter, it is essential to outline that the SE has shaped what is currently known as Shared Mobility, a system that has provided society with a new means of transport (The Sharing Economy in Europe, 2022). Shared mobility, is then, a type of shared economy that aims to optimise the use of mobility resources that are mainly accessed through the Internet.

The development of the SE, together with the constant search for more sustainable cities, has led to a situation in which Smart Mobility systems are gaining great importance and interest from the public, as it is one of the main building blocks for the development of smart cities. Therefore, carsharing is becoming crucial when tackling the topic of cities' transitioning into smart cities.

Thanks to various studies, it has been made clear that carsharing has a positive impact not only on the quality of urban life but also on the environment, as it reduces the adverse effects of current transport. It is worth mentioning that these studies have generally focused on quantifying the benefits of carsharing, as well as explaining how carsharing supports the penetration and adoption of electric vehicles. What's most, they also address issues related to increasing the profitability of carsharing companies through issues such as vehicle relocation.

However, this paper tries to take one step further, and promote the use of carsharing by considering the adverse effects of it as new opportunities of growth. For example, in order to ensure carsharing success in the long run, latent demand must be addressed and accessed (Review of the Impacts on the Automobility Market, 2017). If the latter is achieved, private vehicle utilisation would be reduced considerably and the transition towards smart cities would be significantly favoured.

There are various ways in which latent demand could be tackled. Some studies have used multi-agent simulation tools (MATSim) to observe user demand and provide an optimisation tool for carsharing companies (Carsharing Demand Estimation, 2015); other studies have suggested deployment strategies not only to reduce expenses, but also to increase service provided to users (Deng & Cardin, 2018); whereas some researchers have focused their studies on demand estimation to select the optimal location of charging infrastructures for Electric Free-Floating Car-Sharing vehicles (Gallardo , Otero , & Jiménez Octavio, 2021). After a thorough review of different articles, a precise demand estimation is needed in order to better understand where do carsharing companies perform poorly, and why don't they reach customer requirements.

Even though the approaches mentioned above are effective when considering increase in user demand, various studies have investigated such problem and found a solution that could potentially decrease latent demand, therefore increasing user demand considerably. This approach aims to reduce burdens suffered by users when using carsharing vehicles, such as time spent when parking these cars, while maximising the benefits of carsharing companies. This solution involves maximising the benefit from a fair and appropriate distribution of parking spaces dedicated exclusively to shared-mobility vehicles.

Generally, such studies are being driven by local governments, such as the cities of Sydney (Sydney, 2022) and New York (DOT, 2021). The latter has demonstrated that by targeting certain parking spaces (especially those in areas with high concentrations of private parking), not only has latent demand been significantly reduced while the profit of these companies has increased, but also both blocked space reports and greenhouse gas emissions have decreased (DOT, 2021). Without a doubt, on-street parking spaces are utilised more effectively (Sydney, 2022). However, cooperation between carsharing companies and local governments is a must regarding carsharing promotion. For example, the city of NY has required that 20 % of carsharing vehicles are placed on on-street carshare spaces in DOT-defined equity areas to ensure a good distribution of this mobility service throughout the entire city (DOT, 2021).

Other studies have developed this matter further, emphasising the benefits of renting parking slots for carsharing companies by modelling a mathematical optimisation algorithm that evaluates where should these slots be allocated. In particular, the work carried out by Carrese et al. (2021) pursues this goal. By providing an insight on why parking policies in cities are crucial to carsharing success, their work proposes an optimisation approach based on genetic algorithms that best allocates parking slots throughout the city of Rome (An optimization model and genetic-based matheuristic for parking slot rent optimization to carsharing , 2021). What's most, the model developed aims to find a balance between the societal welfare and the interests of carsharing companies. Therefore, restrictions regarding the number of parking slots that can be rented in a certain district are implemented, amongst other things.

Following Qiuyue et al. (2020), due to the limited resource allocation, it is a must to establish a fair location for carsharing stations as efficiently as possible. In their study, they present an optimization model that analyses the best distribution for electric carsharing vehicles' location, while maximising user demand. Several constraints such as parking prices have been taken into consideration and the city of Lanzhou, China has been chosen as a study case. To pursue their objective, an optimisation problem based on genetic algorithms is employed, and oversees allocating carsharing cars regarding travel demand (Optimal Model for Carsharing Station Location Based on Multi-Factor Constraints , 2020).

Throughout the years, more and more cities across the world are joining the phenomenon of establishing reserved parking slots for carsharing vehicles uniquely; therefore, giving importance to a city's transition to a smart city. San Francisco Bay Area can be described as the pioneer of the carsharing parking policy (Shaheen, Cohen, & Martin, 2009). Later, cities such as NY, Sydney, Ashfield, Calgary, Vancouver, Milan, Rome and Turin have developed regulations favouring carsharing vehicles (An optimization model and genetic-based matheuristic for parking slot rent optimization to carsharing , 2021).

As for Spain, no city has yet summoned to having such a refined policy regarding carsharing, even though the government is starting to implement various solutions. For example, the community of Madrid is trying to implement parking spaces for the exclusive use of carsharing companies. In fact, in 2020 a project was launched in IFEMA consisting of 12 parking spaces reserved exclusively for shared mobility vehicles (Ribas, 2022). This car park turns out to be the first of its kind, although the government wants to establish more such car parks around Madrid.

Therefore, this paper will evaluate which municipal car parks will be the most suitable to reduce both private car use and latent demand. In order to do so, this work will mainly rely on the studies developed by Carrese et al. (2021), and Qiuyue et al. (2020) which implement optimisation models to that detect which parking clusters should be rented by carsharing companies in order to increase their profit. In this way, a similar model will be implemented to make Madrid a more sustainable and smarter city. What’s most, the study carried out by Gallardo et al. (2021) will be crucial when developing the model that is going to be implemented.

2.2. GENETIC ALGORITHMS

2.2.1. INTRODUCTION

In today's day and age, different disciplines such as economics, politics, and engineering are trying to solve real-life problems. However, on most occasions these problems are somewhat complex, therefore a different approach to traditional applications must be considered. This is where metaheuristic algorithms play a huge role, as they are thought to be the best approach to solving real-life, complex problems efficiently.

One of the main characteristics of metaheuristic algorithms is that they are inspired by various fields such as biology (especially by evolutionary processes), and the laws of physics. Regarding the number of possible solutions available, metaheuristic algorithms are divided into two main groups: single-solution-based metaheuristics and population-based metaheuristics (Katoch, Chauhan , & Kumar, 2020). The former regards a unique solution; whereas the latter regards multiple solutions, to avoid getting trapped in local optima. Moreover, among the population-based metaheuristics, evolutionary and swarm-intelligence algorithms are well-known algorithms. This classification can be better visualized in the following figure:

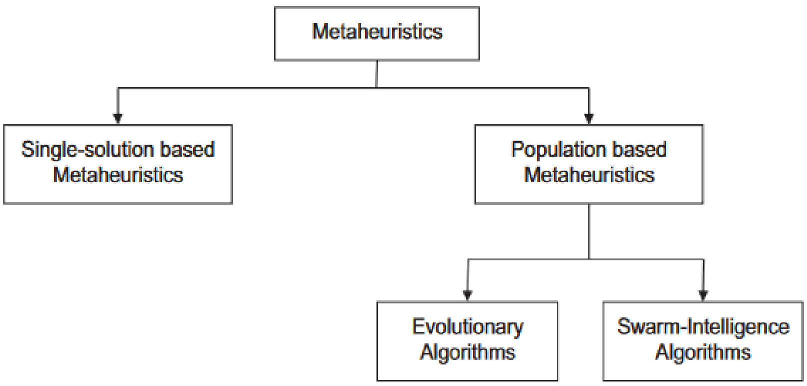


Figure 1- Classification of metaheuristic algorithms (Katoch, Chauhan and Kumar, 2020)

There are various well-known algorithms such as ant colony optimization (ACO), or part swarm optimization (PSO). However, this section will focus on the Genetic algorithm (GA), an evolutionary algorithm that was first developed by John Holland in the 1960s (Yang, 2020) that was aimed at solving optimization problems and search problems by generating high-quality solutions.

The classical GA is inspired by Charles Darwin's theory of natural selection, where the concept ''survival of the fittest'' is employed (Katoch, Chauhan , & Kumar, 2020). The procedure followed by GA is the following. There is an initial population of individuals (n chromosomes) that are randomly initialized. These individuals undergo a series of interbreeding and mutations to evolve into species that are better suited to the environment in which they develop. In other words, fit individuals survive, and unfit individuals die. What must be made clear is that species have specific genetic information that is locked up in their genome. This information consists of a chain of chromosomes, made up of genes, that contains the DNA of the individual, which will be later used in the reproduction of individuals. According to the fitness function, two fit chromosomes are selected from the population during the reproduction process. Parents' genes interbreed applying the single-point crossover operator with the crossover probability, forming new chromosomes and thus new offspring. Thereafter, the offspring is susceptible to mutations that cause their DNA to change (by applying the uniform mutation operator with mutation probability). Once the latter has been accomplished, the new offspring will be placed in a new population where the selection, crossover, and mutation processes are then computed repeatedly until the best possible solution is obtained. All in all, the key elements of the GA are chromosome representation, selection, crossover, mutation, and fitness function computation (Katoch, Chauhan , & Kumar, 2020), and will be further developed thoroughly.

For any optimization algorithm to be efficient, the GA must combine two basic parameters: exploration, understood as the investigation of new and unknown individuals found in the possible solutions; and exploitation, where, with the existing knowledge, better solutions are found. Having a correct combination of both, the GA will achieve its main purpose: to optimize functions characterized by having several variables to optimize or deal with non-linear and constrained problems.

2.2.2. PHASES OF GA

To get a better understanding of the sequence followed by Genetic Algorithms, a flow chart will be presented in Figure 2- Genetic Algorithm flowchartFigure 2.

As a first step, there is a generation of an initial population composed of n individuals. These individuals are also known as chromosomes and are possible solutions to the proposed problem. After, individuals will be assessed according to a fitness function that will indicate whether individuals are eligible or not. What must be taken into consideration is that the most suitable ones will be selected and crossed with each other, giving rise to a new population that will replace the previous one. The generation of this new population will be the starting point of the second iteration, and so on.

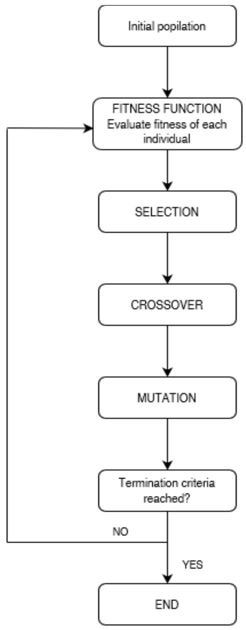


Figure 2- Genetic Algorithm

The number of iterations completed in the GA will be determined in line with computational costs, and the cut-off criteria that are going to be implemented. Moreover, the execution time must be sufficient to explore the right number of solutions.

INITIAL POPULATION

This phase is characterized by the generation of a random population of n individuals that arises from a series of random number strings (usually binary), each of which represents an individual in the population. Each individual is a possible solution to the problem and the strings of numbers are the rows of the population matrix. What's most, the generation of the initial population will be only performed in the first iteration.

The generation of the population comes from a Gaussian random distribution (Mirialili, 2019). So that there is more diversity and various solutions are included, these solutions are scattered homogeneously in the search space. With this, the chances of finding promising and optimal solutions will be increased considerably.

During the generation of the initial population, it is extremely important to ensure that diversity is maintained. If the latter is not accomplished, it may lead to a phenomenon known as premature convergence (Population Initialization in Genetic Algorithms , 2022). This consists of converging into a solution before the optimal solution is reached, and the algorithm is entrapped in local optima. This phenomenon is mainly characterized by parents that generate offsprings that are inferior to them. The reasons to which this occurs are lack of diversity and overly exploitation of existing building blocks (Population Initialization in Genetic Algorithms , 2022) in the population.

To avoid premature convergence, some strategies can be implemented, such as:

- Increasing population size. However, if this number is extremely large, it can lead to a loss of efficiency while the algorithm is being processed.
- Individuals that are alike can be substituted.
- Implement fitness sharing. Individuals that have comparable fitness are segmented.

To initialize a population in the genetic algorithm, there are two main methods: random initialization and heuristic initialization. However, the best approach is to implement the heuristic initialization and use initial good solutions when constructing the population.

EVOLUTION OF POPULATION

In the population that has been generated as a first approach to completing the genetic algorithm, individuals are differentiated and characterized by their genetic information. This information is encapsulated in their genome, which consists of a chain of chromosomes that are made up of genes.

What's most, these genes contain the DNA of the individual in question, which is codified using binary encoding. This type of encoding is the most frequently employed in GA because of its ease of implementation; it also represents one of the most important elements in GA since the velocity to which the optimum is reached is extremely dependent on this stage. Other encoding schemes employed in GA are octal, hexadecimal, permutation, value-based, and tree (Katoch, Chauhan , & Kumar, 2020).

What must be taken into consideration is that the designer of the GA must have a broad knowledge and control of the variables, so the GA is encoded and decoded correctly.

Fitness Function

The fitness function is related to what is going to be optimized (it may sometimes coincide with the objective function). When aiming at maximizing the objective function, it will assign higher values to those chromosomes that are a better fit, while lowering those ones that are worse. With the fitness function, each specific value in the chromosome will be evaluated.

Depending on the type of optimization problem that is going to be evaluated (for example, some functions allow any range of solutions; whereas there are others that contemplate restrictions and do not allow certain solutions as valid), the fitness function may contain a penalty or not. This project will evaluate the case in which restrictions are implemented, therefore evidence regarding the existing constraints must be introduced in the fitness function to ensure there is presumed infectibility in invalid solutions.

To include the latter in the fitness function, the following aspects will be taken into consideration:

- Restrictions must be presented as: $g_i(x) \leq 0$.
- Two multiplicative factors will be introduced:
    - ❖ C, a binary number that will have the value of 1 if the constraint is not satisfied, and 0 in the other case.
    - ❖ K, a real number whose value depends on the weight the designer wants to give to the solutions that do not meet the criteria imposed. In general, a change of the value of K is desired throughout the whole process, having smaller values of K in the initial iterations, and gradually increased ones as iterations go by.

Selection

This step of the GA relies on natural selection, understood as a process where species that are fitter contribute more to the creation of future generations (Population Initialization in Genetic Algorithms , 2022). This process is of extreme importance because the individuals that will participate in the reproduction process will be determined. In other words, elite individuals will be selected to ensure that the optimal solution is reached as quickly as possible.

To carry out this process, there are various approaches that could be implemented. The choice of the latter will depend both on the kind of problem that is going to be issued and on the designer's will. Among the main selection techniques, it is possible to distinguish between roulette wheel, rank, tournament, Boltzmann, and stochastic universal sampling (Katoch, Chauhan , & Kumar, 2020).

In particular, this paper is going to focus on the tournament selection, developed by Brindle in 1983 (Katoch, Chauhan , & Kumar, 2020). This selection strategy functions as follows: there is a tournament in which a determined number of individuals, say K-species, compete against each other, as if they were in a tournament. The fittest contestants will move on to subsequent generations, until there is a final round where winners will be selected to participate in the following processes of the GA. This type of strategy is characterized by a parameter called selection pressure (Genetic Algorithms - Parent Selection, 2022), which measures the probability of an individual participating in the tournament. With that being said, unfit individuals will have lower chances of getting selected to participate in the competition. This type of procedure is gaining a lot of fame due to the fact that it can run with fitness values that are negative (Genetic Algorithms - Parent Selection , 2022). Figure 3 provides an example of how tournament selection works.

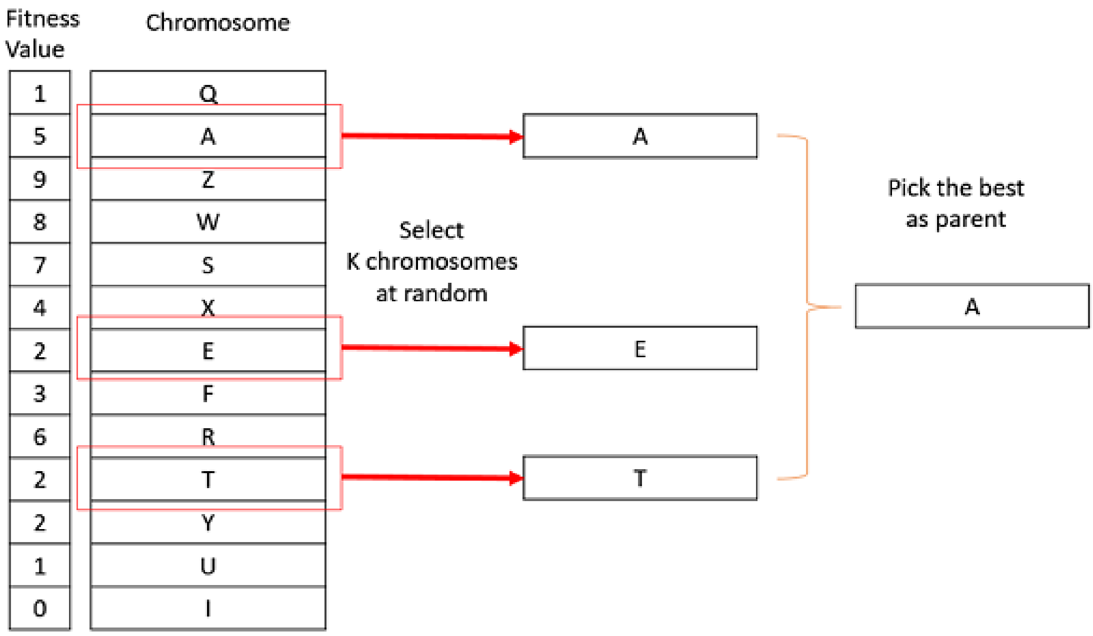


Figure 3- Example of tournament selection (Genetic Algorithms - Parent Selection, 2022)

Crossover

This stage is extremely related to the previous one and aims at producing a new generation that derives from the reproduction of the parents. What must be made clear is that these parents are selected randomly from the population generated during the selection stage.

The reproduction process consists of a combination of the genes found in the male and female partners to produce and give birth to a new chromosome, known as the offspring (Katoch, Chauhan , & Kumar, 2020). Therefore, the crossover stage will mimic the natural reproduction process by combining the parents' chromosomes and generating two solutions from them.

One parameter that must be taken into consideration while conducting the crossover stage is the crossover probability p_c. This parameter represents the amount of times crossover occurs when generating the generation (Hassanat, et al., 2019). For example, $p_c = 100\%$ means every offspring in the generation has been created by crossover. Generally speaking, the crossover probability has a value of 0,7.

Among the crossover techniques that are found in practice, it is possible to distinguish between: the single-point, k-point, uniform, partially matched, order, precedence preserving crossover, shuffle, reduced surrogate, and cycle (Katoch, Chauhan , & Kumar, 2020). However, the partially matched crossover (PMX) is the most used due to the fact that it is the technique that better operates. In order to better understand how this crossover works, an example will be provided below (Desjardins, Falcon, Abielmona, Petriu, & Emil, 2017).

- As a first step, the crossover range will be randomly selected

Parent 1	1	2	3	4	5	6	7	8	9
Parent 2	5	4	6	9	2	1	7	8	3

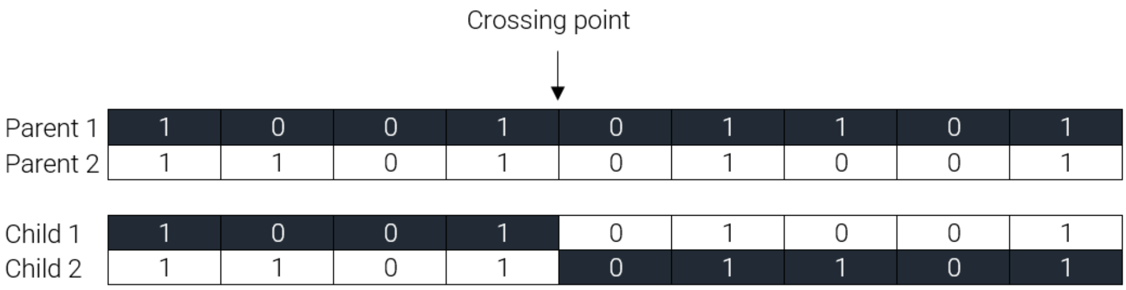
- The second step consists of the combination of the parents' genetic information in order to generate a new offspring

Child 1	1	2	6	9	2	1	7	8	9
Child 2	5	4	3	4	5	6	7	8	3

- During the third phase, the mapping relationship will be established. In this case:
  1↔ 6↔3
  2↔5
  9↔4
  Therefore:

Child 1	1	5	6	9	2	1	7	8	4
Child 2	2	9	3	4	5	6	7	8	1

Among other typical methods, it is possible to find the single-point crossover method. The latter consists of selecting a gene from the parents' chromosome, proceeding to the creation of the offspring as follows: the genes comprehended between the origin of the chain and the selected one of the first parent are copied to the first offspring, whereas the remaining genes of the second parent are copied to the other part of the offspring's chain. **Error! Reference source not found.** shows the procedure followed in the single-p oint crossover method.

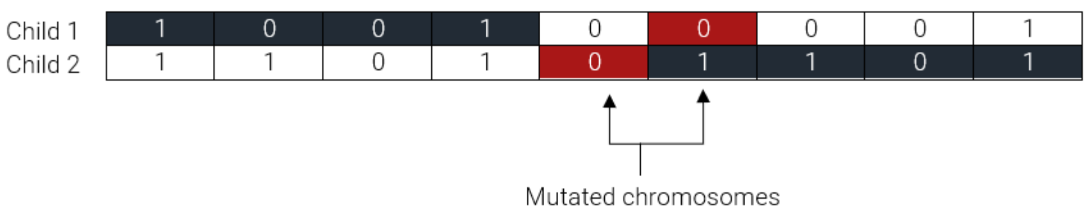


Once the children have been generated, the new population can be formed in different ways: either by considering the offspring directly as members of the new population (parents would then disappear); or by implementing the niche crossover mode. The latter includes the two best chromosomes (as a comparison between offspring and their relative parents) to the new population; therefore, improving the fitness of the evaluation function.

Mutation

This is the last step of the GA and consists of the random alteration of one or various genes within the offspring's chromosomes. For better or worse, the offspring will change its characteristics. Therefore, this stage is responsible for preserving the genetic variety from different populations (Katoch, Chauhan , & Kumar, 2020).

The parameter to be specified in this stage is known as mutation probability p_m, and is responsible for indicating the degree to which mutation occurs within a population. In general, this parameter must have a low value (around 0,03) so that individuals are not distorted. However, this parameter is of extreme importance due to the necessity of having diversity within the populations.



Once this stage has been completed, the first iteration comes to an end and the population generated during this phase will become the initial population of the next generation.

3. CHAPTER 3. MATERIALS AND METHODOLOGY

Without a doubt, urban mobility in cities should be improved considerably. The latter could be achieved through the spread of carsharing. Therefore, this report aims to increase the use of carsharing as a principal means of transport through the implementation of a mathematical optimization problem. Without a doubt, the problem that is going to be tackled is a major problem for local governments. Thus, this project will provide a user-friendly mathematical tool for local governments that can be easily adopted and adjusted.

This research will focus principally on the allocation of parking slots destined to carsharing companies exclusively. Therefore, users will be able to park carsharing vehicles without spending too much time and money on the search for parking slots throughout the city. With this, finding a parking space in a certain area won't be either costly or time-consuming.

Several studies that have been conducted reveal that carsharing membership is dependent on the location of stations (Ciari, Weis, & Balac, 2016). Therefore, this report aims to go one step further and optimise the location of the parking slots that should be destined to carsharing use uniquely.

3.1. OBJECTIVES AND SPECIFICATIONS

It is worth mentioning that the main objective of the project will be to analyse the impact of the reservation of parking spaces by carsharing companies on the latent demand for this mobility service. The case study will be carried out on the city of Madrid, using urban planning and mobility data. In this way, a model will be adjusted to optimise both the number of spaces required and their location.

Among the objectives of the project to be highlighted, it is possible to find:

- To choose the best subset of parking spaces for carsharing companies to rent in terms of latent demand reduction.

- To obtain a fair territorial distribution of parking spaces that meets the needs of the population.

- To find an optimal balance between the interests of the population and those of the for-profit companies.

- To provide a user-friendly mathematical tool for local governments that can be easily adopted and adjusted.

In order to best solve the problem carsharing companies all around the world are facing, a mathematical optimization model will be implemented. The objective is to obtain the best subset of parking slots that best satisfies latent demand, by analysing and reducing the difference between potential and satisfied demand from carsharing companies. To achieve the latter, this study will rely on real rental data from carsharing operators. Therefore, the report carried out by Gallardo et al. will be an important source of information.

What's most, the methodology was coded using Python programming language, and a metaheuristic algorithm was proposed as a solution to the problem. Therefore, this mathematical problem will have both the decision whether to rent a parking slot or not and the number of slots per parking as decision variables.

3.2. DATA

First of all, the area of study will be discretised into rectangular cells, creating a grid that will be composed of m rows and n columns. Figure 4 – Example of discretized area presents an example of how the latter is going to be implemented. What's most, each quadrant will represent a demand point; therefore, the location of the parking areas where slots will be rented will heavily depend on this information.

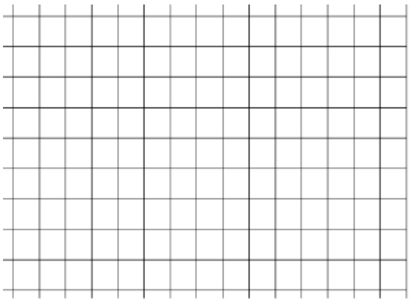


Figure 4 – Example of discretized area (Sai, Bi, & Chai, 2020)

As it has been previously stated, user demand in the study area must be determined in order to best allocate parking slots. Therefore, before coding the mathematical problem, it is essential to analyse both potential and satisfied demand. By doing this, user demand will be determined and the demand matrix of the region in question can be obtained. What must be made clear is that the data needed to obtain user demand will be retrieved from Gallardo et al.'s work, and the demand matrix of the study region will coincide will the discretized grid created during the first step.

Moreover, a matrix that indicates the distribution of the parkings that should be taken into consideration will be created. This matrix, A(x,y), will represent a distribution matrix composed by 0s and 1s, where 1 means that the parking should be included, and 0 means that no slot should be allocated there (Sai, Bi, & Chai, 2020). Therefore, if $a_{xy} = 1$, a determined number of slots will be allocated to that certain parking; if $a_{xy} = 0$, Therefore, the distribution matrix will be created in the following way:

$$A = \sum \mathrm{A}(x, y) \tag{1}$$

3.3. OPTIMISATION MODEL

3.3.1. ASSUMPTIONS

In order to build the optimisation problem, the following assumptions will be taken into consideration:

- Maintenance costs in public parking areas won't be quantified.
- Parking stations where there is no latent demand will not be taken into consideration.

3.3.2. MATHEMATICAL MODEL

This study aims to determine slot allocation in order to increase carsharing user demand. Therefore, to achieve the main goal, the area of study will be discretised into a grid as a first step. Once the latter has been accomplished, the demand matrix will be calculated according to the created grid. To sum up, the mathematical model will be implemented, and a distribution matrix of stations will be obtained as a solution.

As for the mathematical model, the main goal is to obtain the solution that best satisfies the objective function subjected to constraints. The objective function aims to reduce latent demand by comparing both potential and satisfied demand. On top of that, the constraint conditions that will be applied are related not only to cost constraints, but also to maximum and minimum number of slots that can be allocated in a determined parking. To get a better understanding of the functions that will be implemented, this section will thoroughly explain the main components that are crucial when developing the mathematical model.

Objective function

So that profit from carsharing companies increases considerably, user demand should be maximised. Therefore, as it has been previously stated, user demand should be optimised by reducing the difference between potential and satisfied demand. By this, latent demand will be decreased; thus, the objective function aims to maximise the demand following Equation:

$$maxD = \sum_{\mathrm{x}=1}^{\mathrm{m}} \sum_{y=1}^{n} \min A \tag{2}$$

Being A the mean of the latent demand regarding the total number of origin and destination trips in a workday satisfied by carsharing companies. On top of that, it is essential to highlight that latent demand will be calculated as the difference between potential and satisfied demand regarding carsharing services.

Constraints

Constraints are an integral part in the formulation of any mathematical problem. In this study, they will be key when analysing which solutions are feasible or not. However, before presenting the constraints that will be applied in the mathematical model, it is essential to introduce the concepts of penalty functions and repair algorithms, due to the fact that these will be implemented in order to eliminate any kind of infeasible solutions in the genetic algorithm.

Penalty functions are those ones that aim to decrease the fitness value of infeasible individuals in each population generated; therefore, feasible solutions can take precedence over those infeasible solutions in the selection process (Rasjido, Pandolfi, & Villagra, 2010). Thus, the value of the objective function and the constraint are blended into a single value. Equations (3), (4) are penalty functions; particularly, they are partial penalty functions, meaning that a penalty will be applied when the solution is close to the feasibility limit.

On the other hand, it is possible to find repair algorithms. These ones consist of modifying infeasible solutions into feasible ones with the goal of meeting specific constraints. This mathematical approach will implement the Lamarkian approach (Rasjido, Pandolfi, & Villagra, 2010), which consists of modifying non-feasible individuals every time a new population is generated.

The following section will present the penalty functions that are going to be applied:

- <u>Parking fee:</u>

$$C_{PARKING} = \sum_{x=1}^{m} \sum_{y=1}^{n} C_{xy} * t * M_{xy} \tag{3}$$

Where C_{xy} is the cost associated to the parking price for 1h; t is the average time a car is parked in a free station in 1 year; and M_{xy} represents the location of the stations in the region to be studied.

- <u>Maximum and minimum number of parking stations:</u>

$$n_{min} \leq X \leq n_{max} \tag{4}$$

Where X will be the total number of parking stations to be considered when allocating the parking slots. This value will be optimised throughout the optimisation model, and the individual with the highest fitness value will provide this data. As for the values n_{min} and n_{max}, they will be later specified.

- <u>Maximum number of parking slots in the entire city:</u>

$$Y \leq m_{max} \tag{5}$$

Where Y will be the total number of slots allocated throughout the entire city. In the best-case scenario, this number will be equal to m_{max}; however, since the number of parking slots will be rounded, Y could end up being inferior to the established value.

Parking slot location

In order to best determine the number of parking slots that should be rented in each one of the parking stations, the following formula will be implemented:

$$N_{PARKING}(i,j) = \frac{Latent\ demand\ (i,j)}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \sum_{j=1}^{m} Latent\ demand(i,j)} * g \tag{6}$$

Where $N_{PARKING}(i,j)$ is the total number of parking slots that are going to be allocated in each of the grids; and g is the total number of parking slots that will be allocated throughout the entire city.

3.4. ALGORITHM

The algorithm that is going to be implemented is a genetic algorithm. This heuristic algorithm is constantly optimising the problem to be solved, thus obtaining the best possible solution. In the following section, the approach that has been followed will be developed thoroughly.

What must be made clear is that both iteration and calculation processes are complicated. Therefore, to get a better understanding of how the algorithm works, the iteration process that has been implemented is shown in Figure 5.

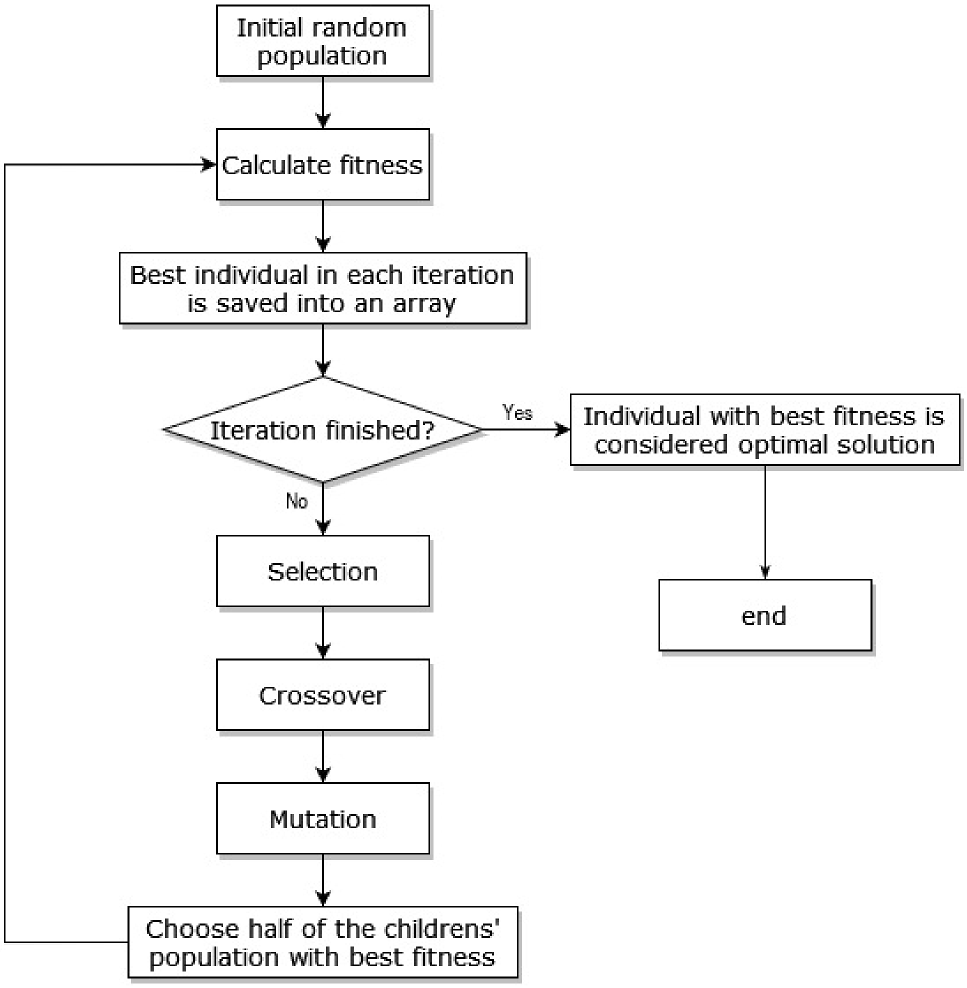


Figure 5 – Iteration process followed in the genetic algorithm

As a first step, an initial population will be adjusted randomly. This population will consist of a determined number of individuals (chromosomes) that will be later adjusted. Each chromosome will be composed of a matrix with m rows and n columns (sizes are equal to those of the grid previously created). Due to the fact that the chromosome will be randomly initiated, it will be essential to adjust such individual so that it is a feasible one. In other words, some values in the grid will always be 0, as there are no parking stations in that determined cell.

Once the latter has been implemented, the next procedure will be to calculate the fitness value of each single individual in the population. To accomplish this, and due to the fact that the objective function is to minimise latent demand (by maximising overall demand), the fitness function will be the same as the objective function. Therefore, the equation that will be implemented is shown in Equation (7) (Proofs of max and min formulas for 2 numbers, s.f.). What must be made clear is that the activity will be measured according to origin/destination events. Therefore, the objective function will rely on latent demand calculated as the mean between trip departure and trip destination events during a workday for each zone in the mesh.

$$\sum_{\mathrm{x}=1}^{\mathrm{m}}\sum_{y=1}^{n}\min A = \sum_{\mathrm{x}=1}^{\mathrm{m}}\sum_{y=1}^{n}\frac{(A_{ORIGIN} + A_{DESTINATION})}{2} \tag{7}$$

Being A_{ORIGIN} the total number of latent trips that are originated in a determined grid, and $A_{DESTINATION}$ the total number of latent trips that end in a determined grid of the mesh.

Once the fitness function has been calculated for each individual, their fitness values will be stored and organised in an array following the next sequence: the fittest will be located in the first position, and so on. The latter will be implemented due to the fact that for each iteration carried out by the algorithm, storing the fittest individual will be useful regarding the search for the optimal solution, as the last individual created may not be the fittest compared to those individuals in other iterations.

During the iteration process, and after obtaining the fitness values of the chromosomes, the selection process will take place. There is a wide range of selection processes; however, this study will execute the tournament selection 11). In this step, there will be an iteration process where individuals will be selected as parents depending on their fitness value. These parents will create the new generation after being subjected to a crossover and mutation process.

As for the crossover process, the multipoint crossover method will be applied. This procedure functions as the single-point crossover process, but the crossover will be applied multiple times across the chromosome. After applying the multipoint crossover process, the children will be generated, and they will be subjected to a mutation process.

During the mutation process, if the random number generated is inferior to the mutation probability, a bit in the chromosome will be inverted. After applying such changes, the loop will start all over again, generating a new population that will be adjusted so their individuals are feasible, and their fitness values will be again calculated.

What must be made clear is that the termination criteria will be established to a desired number of iterations, that will be checked every time the fitness function of a determined population is calculated. Therefore, if the number of iterations is reached, the last population generated will not go through the selection, crossover, and mutation processes.

4. CHAPTER 4. ANALYSIS OF RESULTS

4.1. CASE STUDY: MADRID

The model has been implemented in the city of Madrid, the most populated city in Spain. Without a doubt, Madrid is home not only to locals, but also to people from all over the world. Being an important financial centre, Madrid has become a city of transit, meaning that mobility in the city has increased considerably. A study carried out by Parkimeter reveals that the average parking time of Madrid's citizens is 95h and can reach a total of 125h/year, being the Centre District the most difficult one to park. (El 'carsharing' como pieza clave en la movilidad post-Covid, 2022). The latter, together with 'Madrid 360' air quality plan (Madrid 360 * Madrid 360, 2022), has caused a situation in which transport systems need to be reorganised and updated, so Madrid can become one of the top cities regarding the smart transition.

'Madrid 360' is an environmental sustainability strategy that focuses on reducing the capital's polluting emissions by accelerating the transition of Madrid into a sustainable city. This strategy aims to fight climate change compatible with economic development by promoting the renewal of fleets, the promotion of public transport, integration of new means of transport, and the reinforcement of road safety and innovation.

Moreover, another goal to promote the introduction of electric vehicles in Spain. To this end, there are four methods of action, among which we find the promotion of demand. This work aims to facilitate the promotion of demand for carsharing and, with it, the introduction of electric vehicles in Spain. Therefore, in order to move towards this initiative, the case study has been set up in this city.

4.1.1. MODEL SET UP

Before the parameters associated to the mathematical model are decided, the first step to take is discretizing the city. Figure 6 shows the area to be discretised.

Figure 6 - City of Madrid

According to Gallardo et al.'s study (2021), the area will be divided into a grid using a mesh. Therefore, the operational region will be divided into 324 rectangular cells of 708m height and 380m width (total area of 0.269 km^2). The latter has been implemented as stated due to the fact that it corresponds to the area that is located inside the M-30 (Gallardo , Otero , & Jiménez Octavio, 2021). All in all, the study area will be divided into a grid composed by a total of 17 rows and 19 columns, as represented in Figure 7.

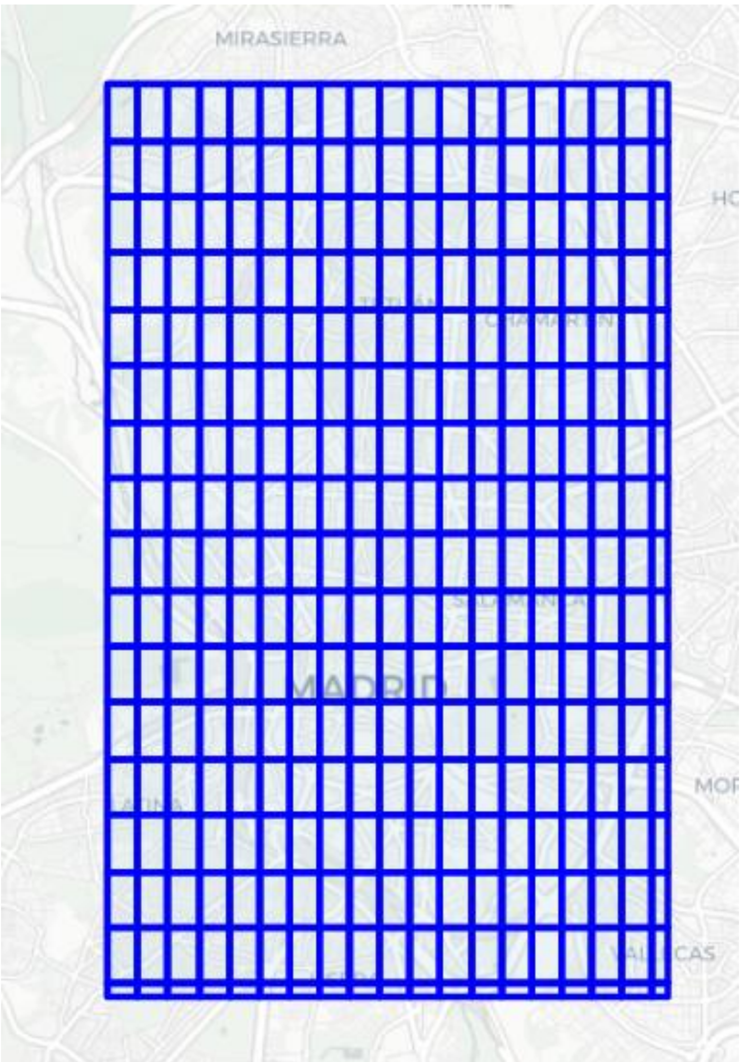


Figure 7 - Grid division in study area

The demand matrix will be obtained from the data retrieved form Gallardo et al.'s paper and will be of great use when calculating the fitness value of each individual. Moreover, the location of the parking stations can't be altered; however, the number of parking slots can be optimised. That is why the location of the parking stations in the city of Madrid will be represented as following matrix K:

$$
K = \begin{bmatrix}
0 & 0 & 0 & k_{0,3} & k_{0,4} & k_{0,5} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & k_{0,15} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & k_{1,5} & k_{1,6} & k_{1,7} & k_{1,8} & 0 & 0 & k_{1,11} & 0 & 0 & 0 & 0 & 0 & 0 & k_{1,18} \\
0 & 0 & 0 & 0 & k_{2,4} & k_{2,5} & 0 & 0 & 0 & 0 & 0 & 0 & k_{2,12} & k_{2,13} & 0 & 0 & 0 & k_{2,17} & 0 \\
0 & 0 & 0 & 0 & k_{3,4} & k_{3,5} & k_{3,6} & k_{3,7} & 0 & k_{3,9} & k_{3,10} & k_{3,11} & k_{3,12} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & k_{4,7} & 0 & k_{4,9} & k_{4,10} & k_{4,11} & 0 & k_{4,13} & k_{4,14} & k_{4,15} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & k_{5,6} & k_{5,7} & k_{5,8} & 0 & k_{5,10} & k_{5,11} & k_{5,12} & 0 & 0 & k_{5,15} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & k_{6,5} & k_{6,6} & k_{6,7} & k_{6,8} & 0 & k_{6,10} & 0 & 0 & 0 & k_{6,14} & 0 & k_{6,16} & k_{6,17} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & k_{7,6} & k_{7,7} & k_{7,8} & k_{7,9} & 0 & k_{7,11} & k_{7,12} & k_{7,13} & k_{7,14} & k_{7,15} & k_{7,16} & k_{7,17} & 0 \\
0 & 0 & k_{8,2} & 0 & k_{8,4} & k_{8,5} & k_{8,6} & k_{8,7} & k_{8,8} & k_{8,9} & k_{8,10} & k_{8,11} & k_{8,12} & k_{8,13} & k_{8,14} & k_{8,15} & k_{8,16} & k_{8,17} & k_{8,18} \\
0 & 0 & 0 & k_{9,3} & 0 & 0 & k_{9,6} & k_{9,7} & 0 & k_{9,9} & k_{9,10} & k_{9,11} & k_{9,12} & 0 & k_{9,14} & k_{9,15} & k_{9,16} & k_{9,17} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & k_{10,6} & k_{10,7} & k_{10,8} & k_{10,9} & k_{10,10} & k_{10,11} & 0 & 0 & k_{10,14} & 0 & k_{10,16} & 0 & 0 \\
k_{11,0} & 0 & 0 & k_{11,3} & k_{11,4} & 0 & 0 & 0 & k_{11,8} & k_{11,9} & k_{11,10} & k_{11,11} & 0 & 0 & k_{11,14} & k_{11,15} & k_{11,16} & k_{11,17} & 0 \\
0 & 0 & 0 & k_{12,3} & 0 & k_{12,5} & 0 & k_{12,7} & k_{12,8} & 0 & 0 & k_{12,11} & k_{12,12} & k_{12,13} & k_{12,14} & k_{12,15} & k_{12,16} & 0 & 0 \\
0 & 0 & 0 & 0 & k_{13,4} & 0 & k_{13,6} & k_{13,7} & 0 & k_{13,9} & k_{13,10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & k_{14,4} & k_{14,5} & 0 & k_{14,7} & 0 & k_{14,9} & k_{14,10} & 0 & 0 & 0 & 0 & 0 & 0 & k_{14,17} & 0 \\
k_{15,0} & 0 & 0 & k_{15,3} & 0 & k_{15,5} & k_{15,6} & k_{15,7} & k_{15,8} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
k_{16,0} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & k_{16,9} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
$$

Figure 8 – Location of public parking stations in Madrid according to the created grid

Retrieving data from Madrid's web page (2022), it has been possible to obtain the exact location of the public parking stations in the city. Therefore, the matrix K represents the location of the parking stations shown in Figures Figure 9 and Figure 10.

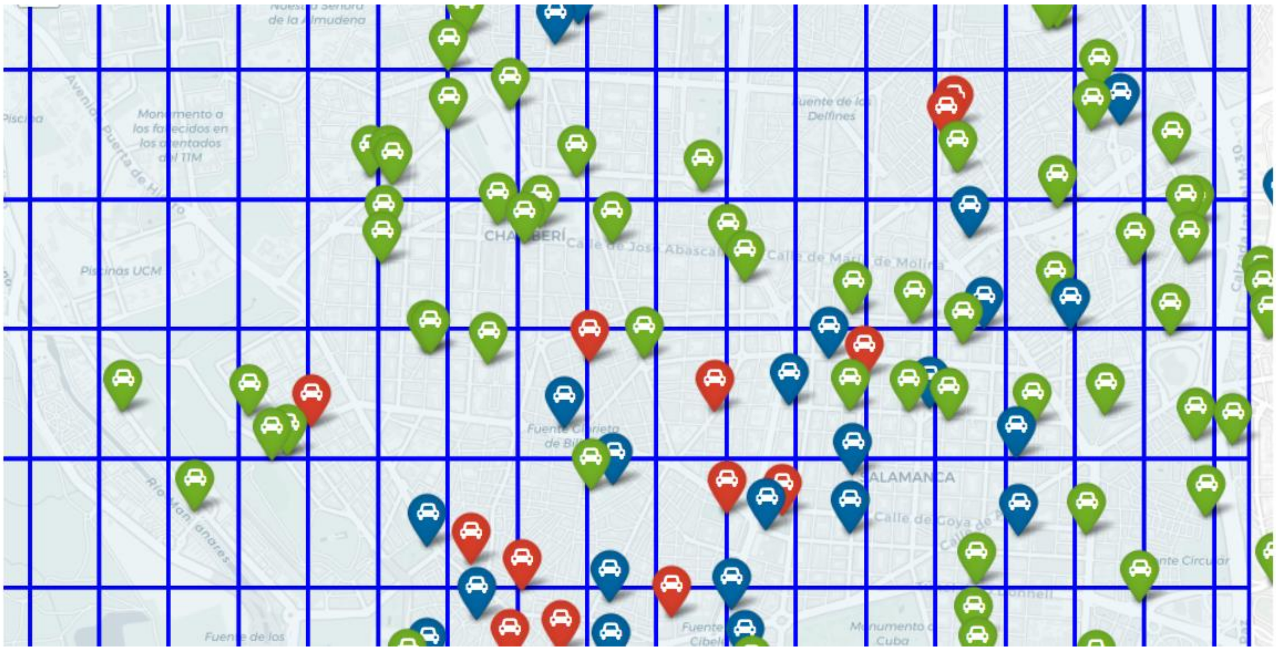


Figure 9 – Location of public parking stations in Madrid (zoom)

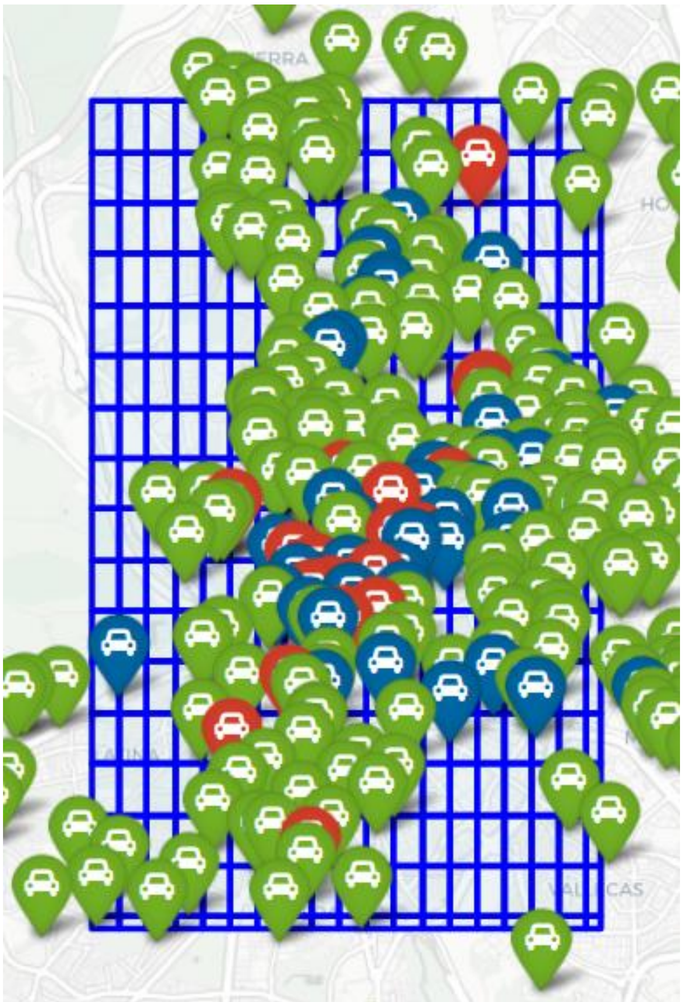


Figure 10 – Location of public parking stations in Madrid

4.1.2. VARIABLE DEFINITION

- User demand in the area to be studied must be specified. From Gallardo et al.'s work, the data regarding potential and satisfied demand in each of the small grids is no longer an unknown.
- Parking fees will have a value of 2.292€/hour in those ones that are mixed and rotational (Tarifas aparcamientos públicos de concesión municipal rotatorios y mixtos - Ayuntamiento de Madrid, 2022).
- As for the residential parking stations, these ones have a fee of 2.05€/month, while those cars that are ECO may have a reduction of 75% over the basic fare. (Servicio de Estacionamiento Regulado (SER). Residentes - Gestiones y Trámites, 2022).

Therefore, the hourly rate of residence has a value of 0.000711€/hour. This value is close to 0, thus it can be considered negligible.

- Moreover, the variables that will be established in the optimisation model will be specified as follows:
  - Total number of iterations: $n_{iterations} = 1500$
  - Total number of individuals in the population: $n_{population} = 600$
  - Crossover probability: $r_{crossover} = 0.8$
  - Mutation rate: $r_{mutation} = 0.05$

4.1.3. CONSTRAINTS

The constraints that will be taken into consideration are those ones in line with Equations (4) and (5). Therefore, this report will implement the following constraints in order to establish the most evenly distributed scenario regarding parking slot allocation:

- Maximum number of parking stations
- Minimum number of parking stations

$$10 \leq X \leq 20$$

- Maximum number of parking slots that will be allocated: $n_{slots} = 50$

4.2. MODEL IMPLEMENTATION

The results of the proposed algorithm will be presented in this section. In order to obtain a more precise solution, the code will be executed a total of 10 times. Not only to verify if there is any kind of similarity between each one of the 10 solutions, but also to test if the code itself may or may not be suitable for providing a solution to the proposed problem. Therefore, to validate the latter, every single parameter will be kept unaltered throughout the entire process.

Once the latter has been explained, it is a must to clarify that the results will be represented with heatmaps, so the results are easily visualised and, therefore, comprehended. Every figure that has been attached in this report is of great use regarding the correct comprehension of the processes that have been implemented. That being said, a summary of what each figure represents will be presented:

Figure 11 exemplifies the overall distribution of latent demand throughout the city of Madrid during a workday. Moreover, following the same pattern, each iteration will show the next figures: the first one will present the heatmap of the overall distribution (as in Figure 12), and next to it, there will be a second heatmap displaying the overall distribution of the parking slots. Both figures will be added one next to the other so both are easily compared. Once that has been presented, a graph showing the maximum fitness value obtained per iteration will be attached.

It is essential to outline that, while carrying out this analysis, the demand was obtained from studying the mean between the origin and destination trips of carsharing companies during a complete workday, therefore different time slots have been considered. Among them it is possible to find: morning peak hour, off-peak, and evening peak hour (Gallardo , Otero , & Jiménez Octavio, 2021). Altogether, it has been possible to represent the total demand, as well as the latent demand in the city of Madrid.

From Gallardo et al.'s report, conclusions were driven into the fact that there are five main hubs whose latent demand is especially noticeable: Barrio del Pilar, Castellana Norte, Salamanca, Moncloa, and Arganzuela, being Barrio del Pilar, the North Castellana axis, and Moncloa (Gallardo , Otero , & Jiménez Octavio, 2021) the top three. Therefore, it is expected that the algorithm places more parking slots in these main hubs.

To get a better understanding of how latent demand is distributed in the city of Madrid, the following Figure has been placed below:

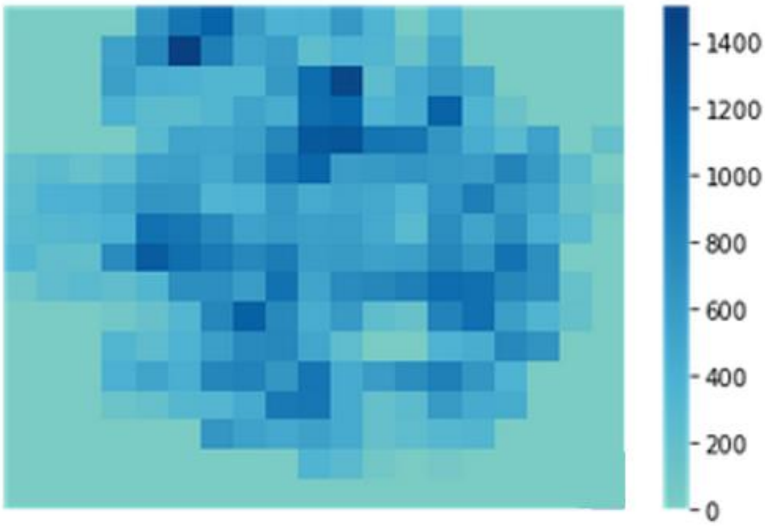


Figure 11 – Latent demand in the city of Madrid

It is essential to outline that, even though it is impossible to meet 100% of the potential demand, citizens would benefit from carsharing services if there was not such a high latent demand in these areas. Therefore, in order to satisfy the latter, a total of 50 parking slots seems reasonable enough to meet such demands.

Results regarding the mathematical model will be presented in the following section.

4.3. RESULTS

This section will present the results of the genetic algorithm. In order to check the feasibility of the proposed algorithm, the code has been run a total of 10 times. What must be made clear is that results will present the best distribution for parking slot allocation per iteration; in other words, it will show the best individual in the population after a total of 1500 iterations. Moreover, its fitness value, the total amount of parking stations to be considered, and the total number of parking slots per parking station will be presented.

By including this information, it will be possible to verify if the implemented code is in line with the characteristics presented by Gallardo et al., which state that the clusters with most latent demand in the city of Madrid are Barrio del Pilar, North of Castellana axis, and Moncloa. Specifically, the cells 26,50, and 87 the ones that where there is a greater amount of originated and terminated latent flows (Gallardo , Otero , & Jiménez Octavio, 2021).

After carrying out the previous analysis, it is possible to conclude with the fact that, even though there is randomness in the model, it allocates more parking slots in those hubs where latent demand is higher. The latter can be easily visualised by comparing the heatmap that represents the overall latent demand in Madrid, and the heatmap that shows where and how many parking slots are going to be reserved for carsharing companies.

As for the fitness function, it can be observed that it does not grow consistently until it reaches a maximum. The latter is because the model has been elaborated in such a way that each time the algorithm creates a new generation, the children are adjusted so they can become feasible solutions.

Moreover, it is essential to choose which solution is going to be the definitive one. Therefore, the individual that is going to be selected as the final solution will be the one that has a considerable good fitness value. Not surprisingly, this solution can be found in iteration #5. Not only is this the individual that has the highest fitness value found in the iterations that have been carried out, but also it’s the solution that has the highest number of parking stations where parking slots are going to be allocated. That being said, it will be interesting to analyse how by changing the restrictions regarding the maximum and minimum number of parking stations can affect the distribution of parking stations in the city. It is essential to outline that results of all iterations will be presented in the Appendix.

4.3.1. Fifth iteration

- The best fitness value obtained was found in iteration #376. The value reached was 11752.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0]
 [0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 0 1 1 0 0 0 0 0]
 [0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 6 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 2 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 0 0 0 0 0 0]
 [0 0 0 0 0 3 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 3 0 0 0 1 3 0 0 0 0 0]
 [0 0 0 0 0 0 4 3 0 0 0 0 0 0 3 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0]
 [0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 2 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 19 parking stations were taken into consideration.
- Parking slot allocation has been distributed as follows:

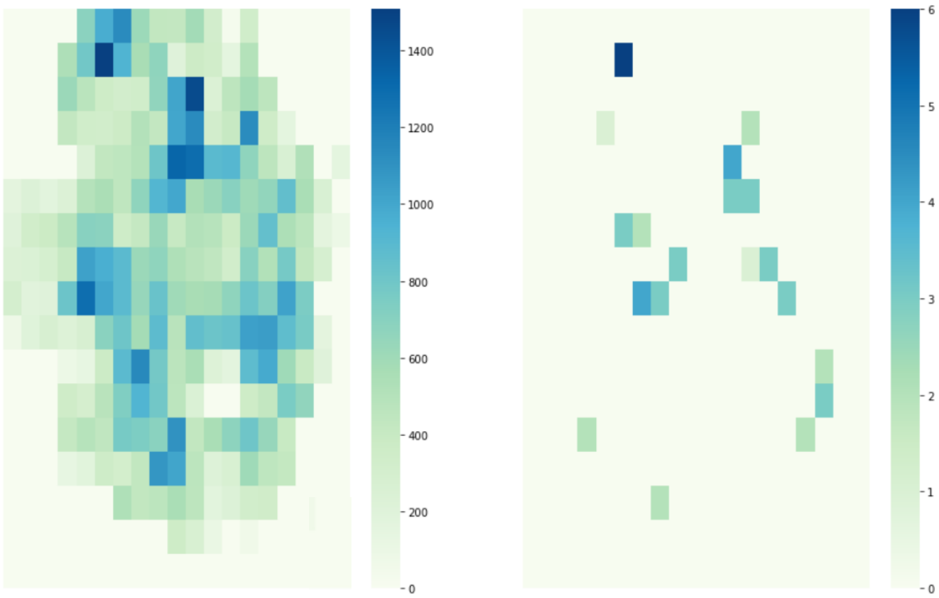


Figure 12 - Parking slot allocation compared to overall latent demand. Iteration #5

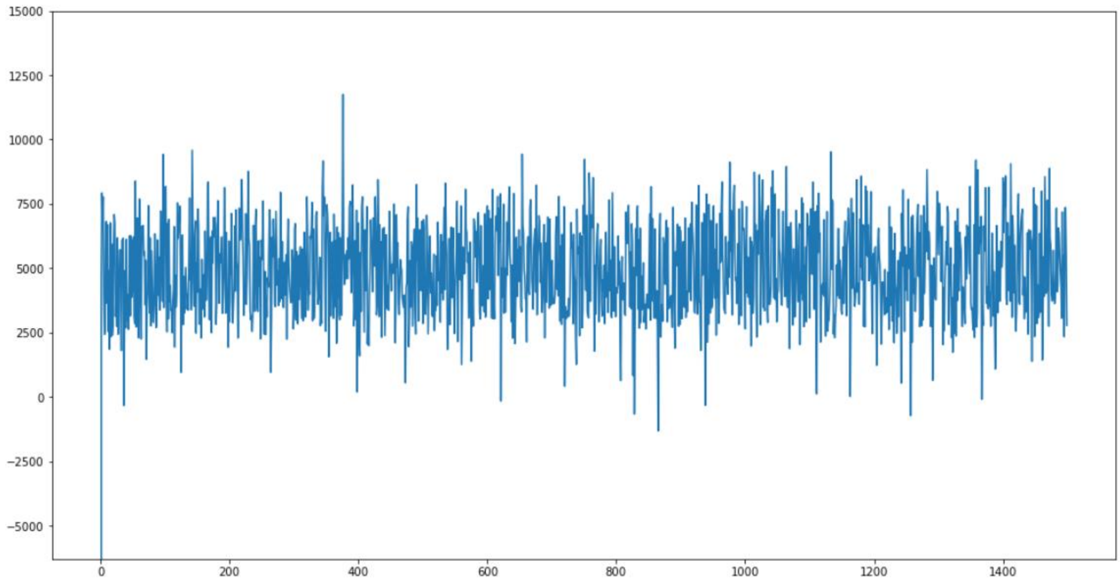


Figure 13 - Fitness function. Iteration #5

Once the solution has been chosen, the next step is to provide information about which parking station are going to be considered in this project. Therefore, the following parking stations will have reserved parking spaces for carsharing companies:

- Parking Sarriá (residents): 6 parking slots
- Parking Aguilar de Campoo (residents): 1 parking slot
- Parking Hurtado Mendoza (residents): 2 parking slots
- Parking Panamá (residents): 4 parking slots
- Parking San Juan de la Salle (residents): 3 parking slots
- Parking Santo Domingo de Silos (residents): 3 parking slots
- Parking Doménico Scarlatti (residents): 3 parking slots
- Parking San Francisco de Sales I (residents): 2 parking slots
- Parking Bravo Murillo (residents): 3 parking slots
- Parking Lagasca (residents): 1 parking slot
- Parking Castelló (residents): 3 parking slots
- Parking Ortega y Gasset (residents): 3 parking slots
- Parking Conde del Valle de Súchil (residents): 3 parking slots
- Parking Galileo (residents): 3 parking slots
- Parking Sainz de Baranda (residents): 2 parking slots
- Parking Estrella Polar (residents): 3 parking slots
- Parking Conde de Casal (residents): 2 parking slots
- Parking Iván de Vargas (residents): 2 parking slots
- Parking Pedro Yagüe (residents): 2 parking slots

This result is very interesting due to the fact that the model has chosen parkings that are of the type ‘Residents’. These parkings are the most suitable ones to introduce reserved spaces to encourage the use of carsharing. However, cooperation from the local government is necessary in order to make this possible. The latter is due to the fact that residents might not like this approach to be implemented (they will have fewer spaces reserved for them), so this is an issue to be considered.

4.4. ECONOMIC IMPACT

In this section, an economical study will be conducted. Here, the capital savings from a carsharing company that no longer must move part of its fleet of carsharing vehicles to increase availability will be evaluated. Therefore, it is essential to consider the number of parking slots that will be allocated through the city of Madrid. During this study, a total number of 50 parking slots will be placed in the different parking stations in Madrid, as it represents 10% of the amount of carsharing vehicles of the company ShareNow in Madrid.

It is essential to outline that the parking stations have been carefully chosen so their complete use is ensured (in the best-case scenario they are in use 100% of the time). That is why this study relies on latent demand, to make sure users can park their cars in potential hubs where there is a high degree of mobility, but not enough parking spaces.

Once the latter has been clarified, the economic impact will take employees that are responsible for the proper functioning of the service into consideration. The latter is due to the fact that fewer employees will be required to move the carsharing vehicles in order to increase their availability in the city (Cordeiro, 2018), since there will be available cars in the potential parking stations that have been chosen.

As it has been previously stated, a total of 50 parking slots will be allocated, therefore, there will be a total of 50 carsharing vehicles that will no longer be transported from their destination point to a potential hub anymore. What's most, from Wednesday 19 December 2018, ShareNow (formerly car2go) users have a fleet of 500 cars at their disposal (Comparativa de carsharing en Madrid. Precios por minuto, 2022). Therefore, taking this into consideration, there could be a reduction of around 10% of workers. This value does not seem realistic, as carsharing vehicles will still need to be cleaned up and maintained. Therefore, the reduction of employees will be subjected to a decrease, and only 70% of the total reduction will be considered. That being said, a total of 7% of the total reduction of employees will be considered. Following Codeiro's report, personal costs per carsharing vehicle amounts to a total of 24,66€/day. Considering this study takes a whole workday into account, carsharing companies will be saving a total of 1,73*50= 86,5€/day. What must be made clear is that the increase in demand per day has not been taken into consideration, meaning that the benefits of carsharing vehicles will increase considerably after the implementation of this methodology.

4.5. SENSITIVITY ANALYSIS

The aim of this section is to provide an analysis on how different parameters may affect the overall distribution of parking slots throughout the city of Madrid, and consequently, how does it affect carsharing operators' performance overall. Therefore, in order to achieve the latter, several case studies will be conducted, from less to more ambitious.

4.5.1. Case Study #1

- The total number of parking slots to be allocated has been increased to 60.
- The maximum number of parking stations that can be considered in the model has been increased to 40

By changing those parameters, the results are as follows:

- The best fitness value obtained was found in iteration #490. The value reached was 15483.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 6 0 0 3 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 2 1 0 0 0 0 0 0 2 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 4 0 2 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 0 2 0 0 0 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 3 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 3 2 0 0 0 0 0 0 3 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 4 2 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 23 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

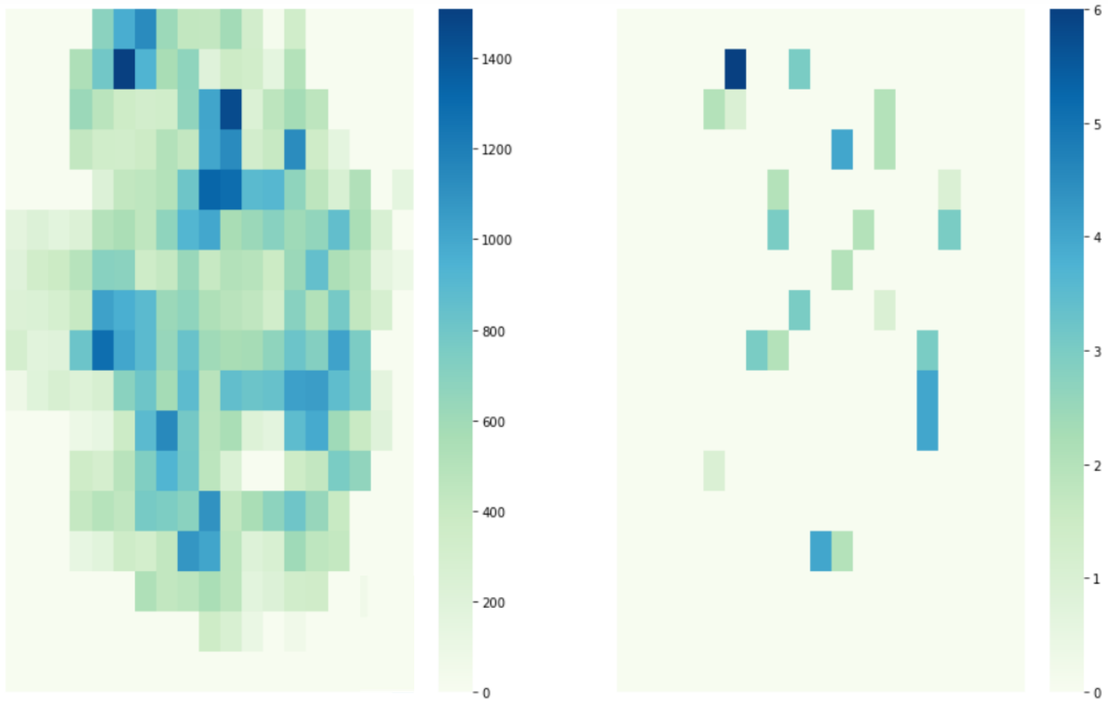


Figure 14 – Parking slot allocation compared to overall latent demand. Case study #1

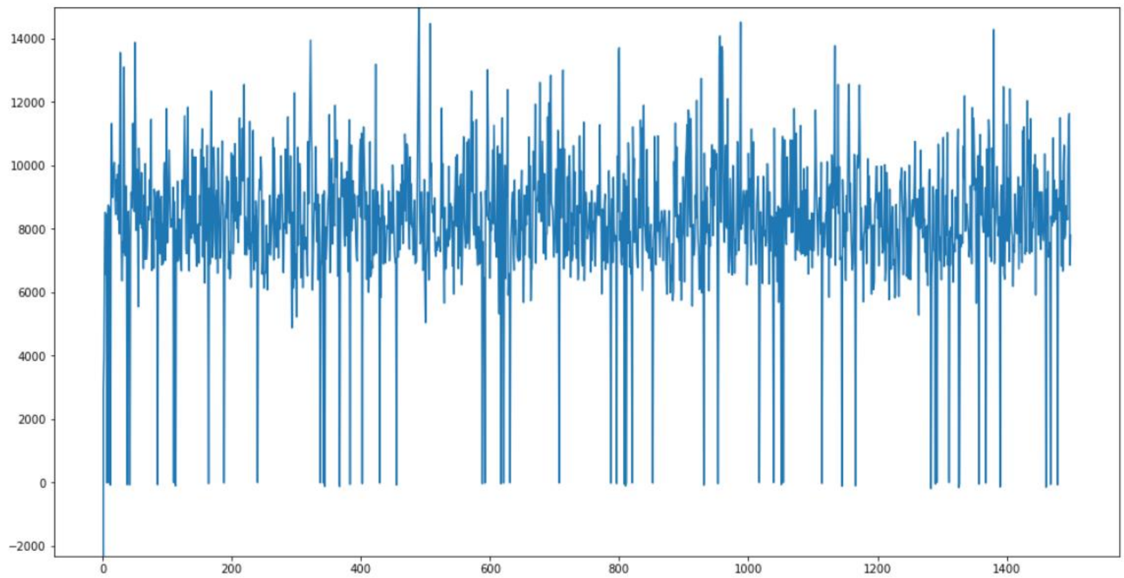


Figure 15 - Fitness function. Case study #1

4.5.2. Case Study #2

- The total number of parking slots to be allocated has been increased to 250.
- The maximum number of parking stations that can be considered in the model has been increased to 50.

By changing those parameters, the results are as follows:

- The best fitness value obtained was found in iteration #552. The value reached was 15411.
- The best individual found in the whole algorithm was the following:

```
Best individual:
 [[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 1 1 1 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

```
Number of parking slots per parking:
 [[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 11  0  0  5  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  6  0  6  0  0 16  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  7  0  0  0  0  0 11  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0 10  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0 14 10 11  9  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0 21  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 12  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 16  0  6  0  0]
 [ 0  0  0  6  0  0  0  0  0  0  0  0  0  0  7 12 11  0  0]
 [ 0  0  0  0  0  7  0  0  0  0  0  0  0 13  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  8  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  7  0  0  7  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]]
```

- A total of 25 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

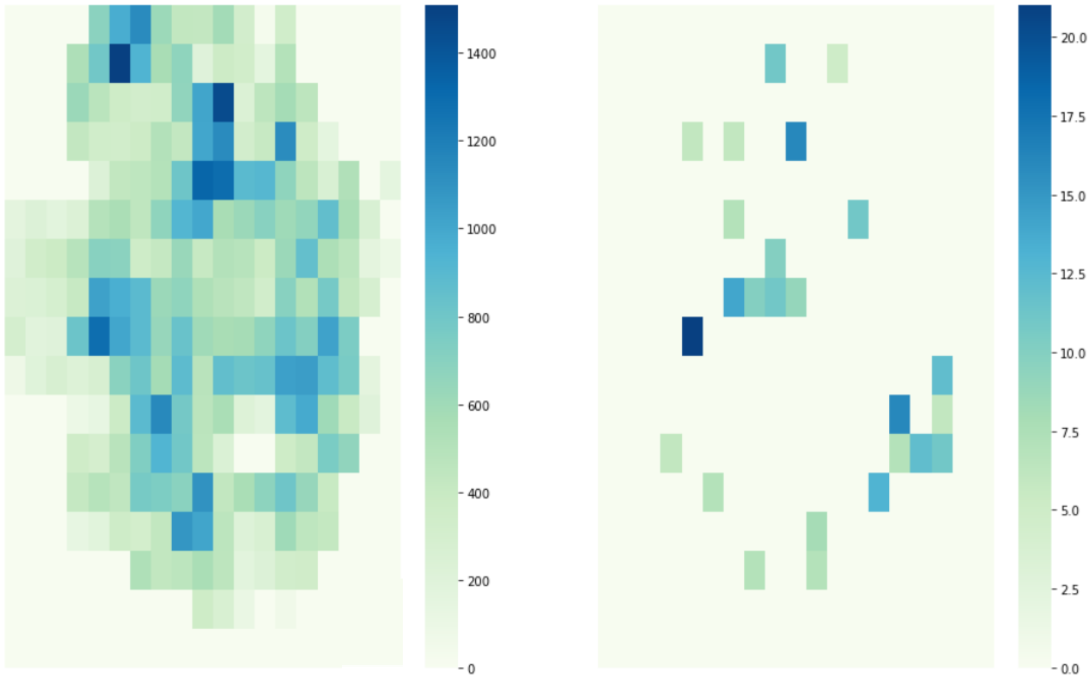


Figure 16 - Parking slot allocation compared to overall latent demand. Case study #2

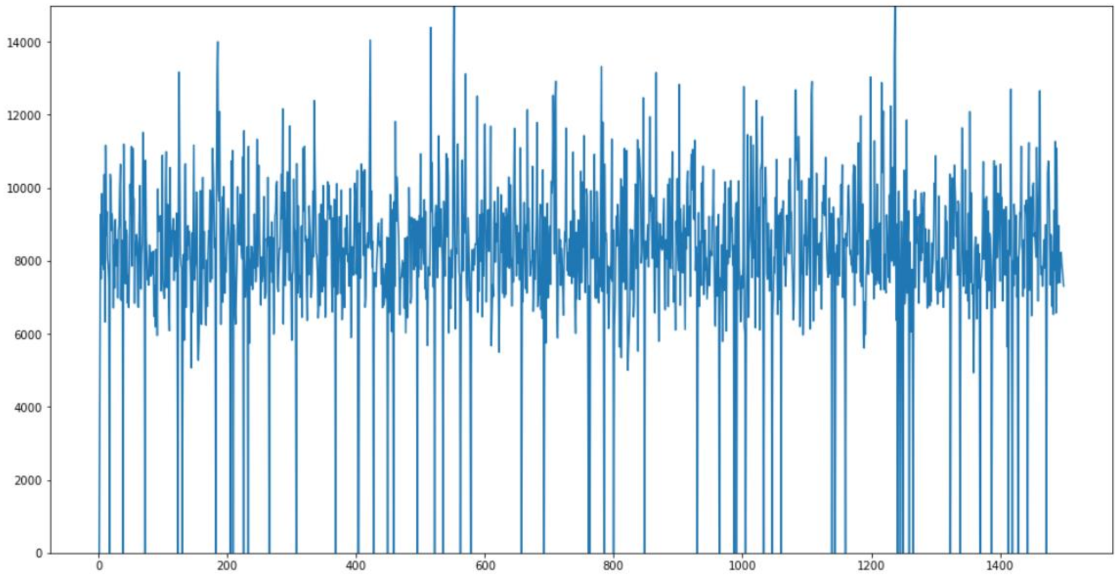


Figure 17 - Fitness function. Case study #2

After conducting the sensitivity analysis, it is interesting to observe that, even though the number of parking slots to be considered increases, the number of parking stations where parking spaces are being distributed does not increase excessively. Not only is the value of fitness function higher in the first Case Study, but also there is a difference of 2 units regarding parking stations to be considered. With this, it is possible to state that to obtain the best outcome possible, the solution will not be to add too many parking stations. What's most, adding too many slots may become a greedy approach and will not be beneficial for carsharing companies in the end.

Moreover, instead of considering more parking stations, the model itself adjusts as many parking slots as possible in several parking stations. For example, the model states that some stations should allocate 21 parking spaces for carsharing companies exclusively. The latter is not coherent nor realistic, as this number is considered to be high in this context. Therefore, the solution is not to increment the number of parking stations, but to optimise this value.

5. CHAPTER 5. CONCLUSIONS

5.1. METHODOLOGY

An optimization problem has been developed with the purpose of reducing wasted time when searching for parking spaces in order to improve not only metropolitan mobility, but also user's welfare. The latter entails an increase in the use of carsharing vehicles in the region where parking slot allocation has been optimised. What must be made clear is that the mathematical model has been developed considering latent demand during one whole workday. And, according to data retrieved from one of the biggest carsharing companies operating in the city of Madrid, implementing this model in that specific region could improve their business' competencies, as it has been demonstrated that there is still latent demand present in the area.

Conclusions regarding results state that the areas where more parking slots should be allocated are: North of Castellana axis, barrio del Pilar, and Chamberí. The latter is in line with the results obtained in the study carried out by Gallardo et al. Therefore, it is possible to ensure that if there are more parking slots allocated in those parking stations, latent demand will be reduced considerably.

If this model was to be implemented in the city of Madrid, the data input should be properly defined in order to ensure its relevance and validity. What's most, is that even though it seems straightforward to implement such solution, legal problems with residents may arise, since they will have fewer spots available to themselves in determining parking stations. However, such a study is out of the scope of this project.

All in all, the main contributions of this research are the following:

- Development and implementation of a methodology that aims to enhance the use of carsharing vehicles.
- Proposal for a quantitative method that allocates parking slots inside public parking stations according to latent demand during a workday. To accomplish such goal, a genetic algorithm has been developed to resolve the issue given the characteristics.
- Economic study of how carsharing companies could benefit from applying this approach.

5.2. LIMITATIONS

The aim of this study is not to provide an exact solution to increasing the use of carsharing by a determined percentage, but to reduce latent demand in such a way that both users and carsharing companies benefit from this situation. On the one hand, if such approach is implemented, users won't have to worry about wasting their time searching for a parking space. On the other hand, carsharing companies will experience an increase in user demand, therefore meaning that their revenues will increase considerably. Even though an economic study has been conducted regarding cost reduction of these companies during a whole workday, the increase in revenues that could be obtained are not quantified. Therefore, the extent to which this study may impact carsharing companies is mere speculation.

Moreover, another limitation to this study is that the data retrieved dates to 2018, signifying that the model could be improved by updating such information. Even though carsharing companies have increased their number of users in these past years, their growth has been altered by the pandemic of 2020. Therefore, it would be interesting to study the current latent demand present in the city of Madrid, since mobility in the city may have experienced some changes.

On top of that, this research only takes data from one of the four carsharing companies operating in Madrid. Therefore, results may not be as precise as if data from every single one of them was collected. Due to difficulty when obtaining information, the method that had to be implemented was the float-based scalation (Gallardo , Otero , & Jiménez Octavio, 2021), as it was the method that resembled reality in the most accurate way.

All in all, the main limitations that can be found in this research are mostly related to the precision of the data that has been collected. Nowadays we live in a fast-changing atmosphere, and that is why updating data will boost the authenticity of the solution.

5.3. FUTURE STUDIES

Future studies could involve evaluating the performance of carsharing companies after the proposed solution is implemented. Therefore, topics such as the increase in user demand, and consequently revenue obtained from carsharing businesses could be tackled.

Another topic that could be addressed would be the implementation of charging stations in the parking stations that have been chosen by the mathematical model. Without a doubt, Madrid is yet to catch up in terms of the amount of charging stations in the city. Therefore, an economic study regarding the implementation of these ones in public parking stations could be extremely useful when promoting the use of carsharing vehicles as a principal means of transport.

Furthermore, this study has been carried out with data retrieved from just one carsharing company. This means that not all carsharing operators in the city of Madrid have been taken into consideration. Therefore, future research could be conducted to evaluate the impact of all four businesses in the area.

All in all, it is essential to outline that the study carried out in this report could be implemented in other cities from all over the world that have not yet developed nor introduced such solutions regarding the transition to a smart city. Therefore, to enhance this transition, other means of transport such as bicycle-sharing systems could be introduced. This study has only focused on carsharing vehicles, thus data related to those specific conveyances should be compiled.

6. BIBLIOGRAPHY

(2022). Retrieved 2022, from https://www.peektraffic.eu/smart-mobility

(2022). Retrieved from https://www.un.org/sustainabledevelopment/es/sustainable-development-goals

Aparcamientos municipales - Aparcamientos públicos - Ayuntamiento de Madrid. (s.f.). Obtenido de Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Circulacion-y-aparcamiento/Aparcamientos-municipales?vgnextfmt=default&vgnextoid=38f87870f3c3b010VgnVCM100000d90ca8c0RCRD&vgnextchannel=b3128fb9458fe410VgnVCM1000000b205a0aRCRD&id

Aparcamientos municipales - Aparcamientos públicos - Ayuntamiento de Madrid. (2022). Retrieved from Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Circulacion-y-aparcamiento/Aparcamientos-municipales?vgnextfmt=default&vgnextoid=38f87870f3c3b010VgnVCM100000d90ca8c0RCRD&vgnextchannel=b3128fb9458fe410VgnVCM1000000b205a0aRCRD&id

Balac, M., Axhausen , K. W., & Clarl, F. (2015). Carsharing Demand Estimation. *Transportation Research Record Journal of the Transportation Research Board*.

BBVA. (2022). Retrieved 2022, from https://www.bbva.com/es/sostenibilidad/el-car-sharing-frente-a-los-retos-de-la-movilidad-urbana-responsable

Carrese, S., D'Andreagiovanni, F., Giacchetti, T., & Nardin, A. (2021). An optimization model and genetic-based matheuristic for parking slot rent optimization to carsharing .

Carrese, S., D'Andreagiovanni, F., Giacchetti, T., Nardin, A., & Zamberlan, L. (2021). An optimization model and genetic-based matheuristic for parking slot rent optimization to carsharing . *Research in Transportation Economics, 85*.

Chi, H.-R., Ho, H.-P., & Lin, P.-K. (2022). Survival strategies of the sharing economy from the pandemic to a new normal: A dynamic capabilities approach. *Wiley*.

Ciari, F., Weis, C., & Balac, M. (2016). Evaluating the influence of carsharing stations' location on potential membership: a Swiss case study . *EURO Journal on Transportation and Logistics* , 345-369.

Comparativa de carsharing en Madrid. Precios por minuto. (2022). Retrieved from Movilidad Eléctrica: https://movilidadelectrica.com/comparativa-carsharing-madrid/

Cordeiro, A. B. (2018). Análisis de viabilidad económica y futuro del carsharing eléctrico en España.

Deng, Y., & Cardin, M.-A. (2018). Integrating operational decisions into the planning of one-way vehicle-sharing systems under uncertainty. *Transportation Research Part C*, 407-424.

Desjardins, Falcon, B. &., Abielmona, R. &., Petriu, R. &., & Emil. (2017). Planning Robust Sensor Relocation Trajectories for a Mobile Robot with Evolutionary Multi-Objective Optimization.

DOT, N. Y. (2021). Carshare parking pilot program. Final report.

Gallardo , A., Otero , Á., & Jiménez Octavio, J. R. (2021). Free-floating Car-sharing Demand Modeling for the Design of a Distributed Charging Infrastructure. Madrid Use-Case.

GeeksforGeeks. (2022). Obtenido de https://www.geeksforgeeks.org/tournament-selection-ga

Hassanat, A., Almohammadi, K., Alkafaween, E., Abunawas, E., Hammouri, A., & Prasath, V. (2019). Choosing Mutation and Crossover Ratios for Genetic Algorithms - A Review with a New Dynamic Approach. *Information*, 390.

Ibánez, P. (2018). *El 97% del tiempo tu coche está aparcado*. Obtenido de xataka: https://www.xataka.com/automovil/el-97-del-tiempo-tu-coche-esta-aparcado

Iberdrola. (2022). Retrieved 2022, from https://www.iberdrola.com/innovacion/smart-cities

innovaspain. (2022). Obtenido de https://www.innovaspain.com/carsharing-coche-compartido-espana

Katoch, S., Chauhan , S., & Kumar, V. (2020). A review on genetic algorithm: past, present, and future . *Multimedia Tools and Applications* , 8091-8126.

Keycafe Blog. (2022). Retrieved from https://blog.keycafe.com/the-history-of-the-sharing-economy/

*Madrid 360 * Madrid 360*. (2022). Obtenido de Madrid 360: https://www.madrid360.es/

Medium. (2022). Obtenido de https://medium.datadriveninvestor.com/population-initialization-in-genetic-algorithms-ddb037da6773

Miguel, C., Avram, G., & Klimczuk, A. (2022). *The Sharing Economy in Europe.* palgrave macmillan.

Mirialili, S. (2019). Genetic Algorithm . En *Evolutionary Algorithms and Neural Networks* (págs. 43-55).

Muller, J. (2022). *Converting a column with coordinates in Pandas to GeoPandas*. Obtenido de Geographic Information Systems Stack Exchange: https://gis.stackexchange.com/questions/378339/converting-a-column-with-coordinates-in-pandas-to-geopandas/378353#378353

Plotting polygons with Folium — GeoPandas 0.10.2+0.g04d377f.dirty documentation. (2022). Obtenido de Geopandas.org: https://geopandas.org/en/stable/gallery/polygon_plotting_with_folium.html

Proofs of max and min formulas for 2 numbers. (s.f.). Obtenido de Physics Forums | Science Articles, Homework Help, Discussion: https://www.physicsforums.com/threads/proofs-of-max-and-min-formulas-for-2-numbers.318767/

Qué es la Cuarta Revolución Industrial y cuáles sus tecnologías - Iberdrola. (2022). Retrieved from Iberdrola: https://www.iberdrola.com/innovacion/cuarta-revolucion-industrial

Rasjido, J., Pandolfi, D., & Villagra, A. (2010). *Algoritmos de reparación para el manejo de restricciones en la planificación del mantenimiento de locaciones petroleras.* UPNA.

revistas.eleconomista.es. (2022). Retrieved from https://revistas.eleconomista.es/digital/2021/enero/el-carsharing-como-pieza-clave-en-la-movilidad-post-covid-CY6054141

Ribas, O. (2022). *Aegfanews.com*. Obtenido de https://aegfanews.com/servicios/945-parking-exclusivo-para-carsharing-en-ifema

Rodríguez, Ó. (2022). *¿Cuál es el barrio de Madrid más difícil para encontrar aparcamiento?* Retrieved from elconfidencial.com: https://www.elconfidencial.com/espana/madrid/2022-03-21/barrio-madrid-mas-dificil-aparcar_3395077/

Rojanakit, P., Torres de Oliveira, R., & Dulleck, U. (2022). The sharing economy: A critical review and research agenda . *Journal Business of Research 139*, 1317-1334.

Sai, Q., Bi, J., & Chai, J. (2020). Optimal Model for Carsharing Station Location Based on Multi-Factor Constraints .

Servicio de Estacionamiento Regulado (SER). Residentes - Gestiones y Trámites. (2022). Obtenido de Sede.madrid.es: https://sede.madrid.es/portal/site/tramites/menuitem.62876cb64654a55e2dbd7003a8a409a0/?vgnextoid=3bbc52afa5ce6410VgnVCM1000000b205a0aRCRD&vgnextchannel=23f9a38813180210VgnVCM100000c90da8c0RCRD&vgnextfmt=default

Shaheen, S. A., Cohen, A. P., & Martin, E. (2009). Carsharing Parking Policy.

Sydney, C. o. (2022). Obtenido de https://www.cityofsydney.nsw.gov.au/public-health-safety-programs/car-share

Tarifas aparcamientos públicos de concesión municipal rotatorios y mixtos - Ayuntamiento de Madrid. (2022). Obtenido de Madrid.es: https://www.madrid.es/portales/munimadrid/es/Inicio/Movilidad-y-transportes/Tarifas-aparcamientos-publicos-de-concesion-municipal-rotatorios-y-mixtos/?vgnextoid=2fa178875ee5e110VgnVCM2000000c205a0aRCRD&vgnextchannel=220e31d3b28fe410VgnVCM1000000b205a0aRCR

Tutorialspoint.com. (2022). Retrieved from https://www.tutorialspoint.com/genetic_algorithms/genetic_algorithms_parent_selection.htm

Wells, P., Liu, H., Maurice, S., Sanvicente, E., & Beccaria, S. (2017). Review of the Impacts on the Automobility Market.

Yang, X. (2020). Nature-inspired optimization algorithms: Challenges and open problems . *Journal of Computational Science* , 101104.

7. APPENDIX

7.1. ALIGNMENT WITH SUSTAINABLE DEVELOPMENT GOALS

The main focus of this work is on line with number 11 of the Sustainable Development Goals (SDGs), which aims to make cities "more inclusive, safe, resilient and sustainable" (Objetivos y metas de desarrollo sostenible , 2022). In this way, cities must commit to environmental security, which is an important pillar of what is known as cities 4.0, or smart cities. It is worth mentioning that more than half of the world's population resides in cities, with 60% of the world's population expected to live in cities by 2030.

If such growth is not controlled through measures imposed by governments to preserve well-being and protect the environment, the consequences can be dire. Not only because cities account for around 70% of global CO2 emissions, but also because they are responsible for 60% of the consumption of existing resources (Objetivos y metas de desarrollo sostenible , 2022).

Therefore, it is vitally important for cities to develop and take the path toward becoming smart cities. This project aims to contribute to this phenomenon by promoting the use of carsharing as a mobility service.

On the other hand, it should be noted that this work aims to contribute to the implementation of SDG goal 13: climate action. The goal of this objective corresponds to implementing preventive measures to reduce or even eliminate the adverse effects of climate change. It should be noted that transport is responsible for one-fifth of the world's total CO_2 emissions. Therefore, carsharing should be fully implemented, as it favours a considerable reduction of these greenhouse gases and means the introduction of more sustainable transport models. In fact, in the not-too-distant future, it is intended that car-sharing vehicle fleets will be made up of all-electric vehicles (Car sharing and the challenges of responsible urban mobility, 2022).

While it is true that the main contributions of this project are in line with the objectives explained above, it is worth mentioning that it will also affect other SDGs, albeit to a lesser extent. Among them, it is possible to find Goal number 3 - health and well-being; Goal number 7 - affordable and clean energy; Goal number 9 - industry, innovation, and infrastructure; Goal 12 - responsible production and consumption.

7.2. RESULTS PER ITERATION

7.2.1. First iteration

- The best fitness value obtained was found in iteration #681. The value reached was 9874.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 1 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 8 5 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 2 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 3 0 5 6 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 13 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

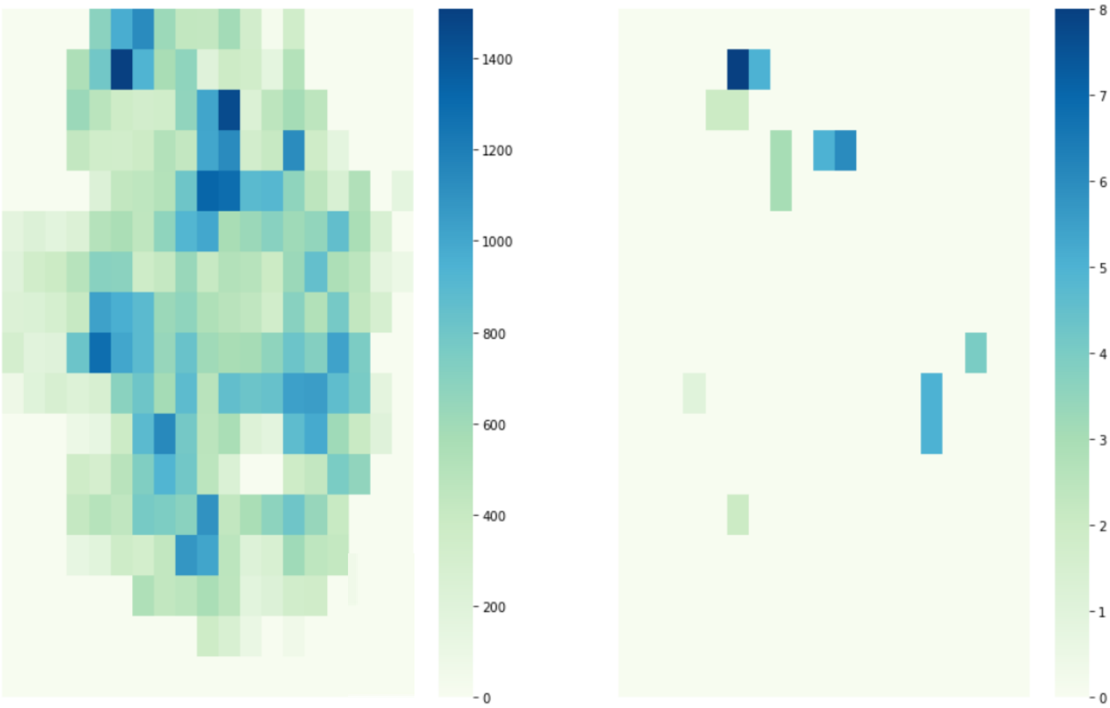


Figure 18 – Parking slot allocation compared to overall latent demand. Iteration #1

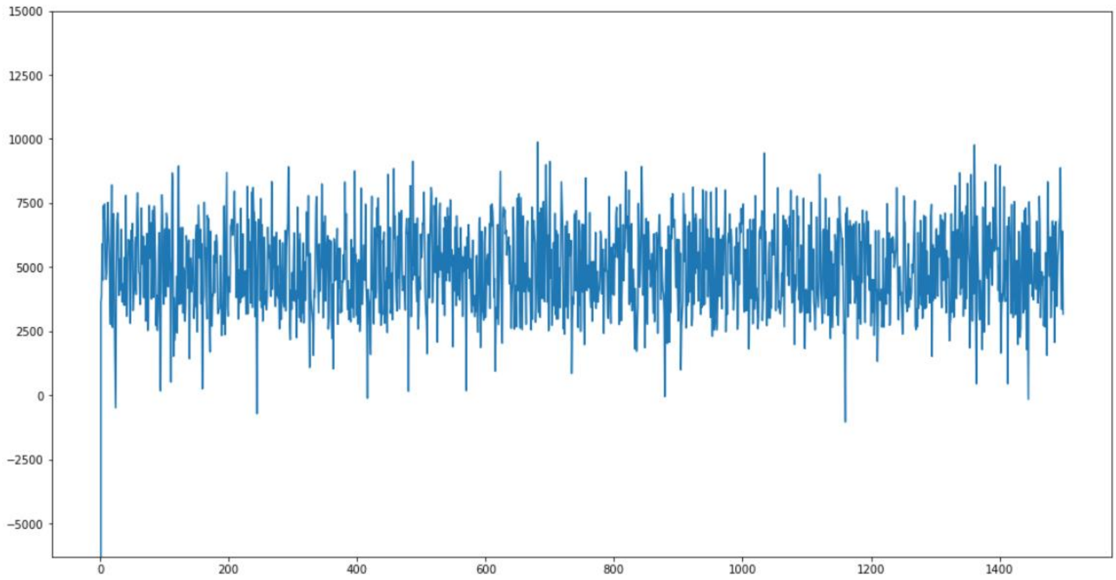


Figure 19 –Fitness value of best individual per iteration. Iteration #1

7.2.2. Second iteration

- The best fitness value obtained was found in iteration #1259. The value reached was 9844.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 8 0 3 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 5 0 0 3 0 0 0 4 0 0 0 0 0]
 [0 0 0 0 7 0 5 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 4 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 14 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

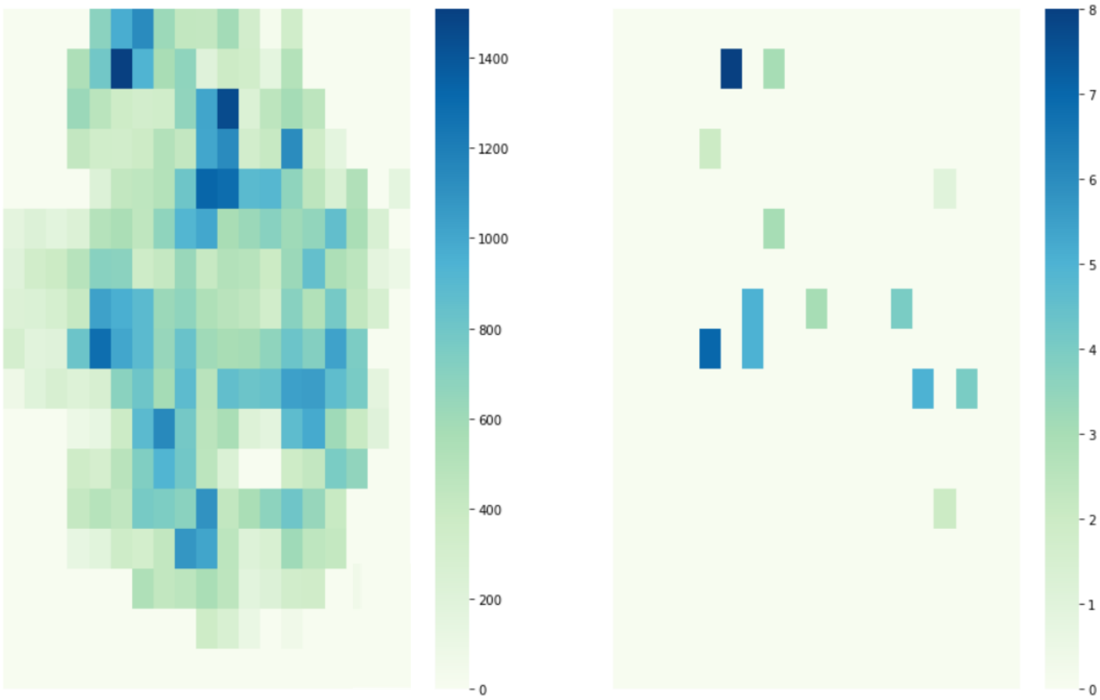


Figure 20 - Parking slot allocation compared to overall latent demand. Iteration #2

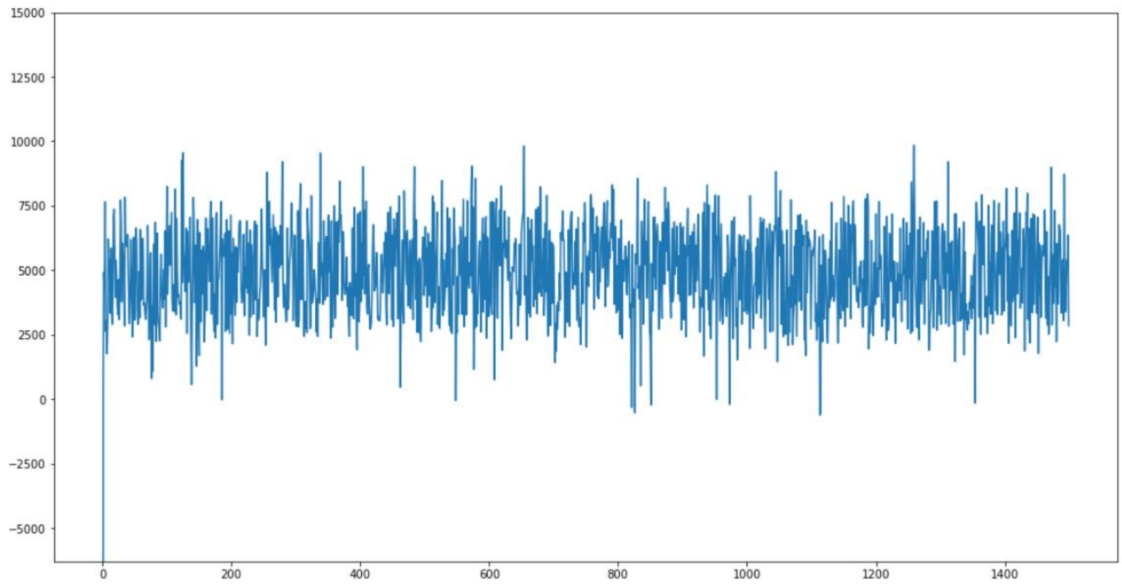


Figure 21 - Fitness function. Iteration #2

7.2.3. Third iteration

- The best fitness value obtained was found in iteration #1042. The value reached was 10025.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 1 0 1 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 6 3 0 2 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 2 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 4 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 3 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0]
 [0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 3 0 0 0 0 0]
 [0 0 0 0 0 0 3 0 0 0 0 0 0 0 3 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 18 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

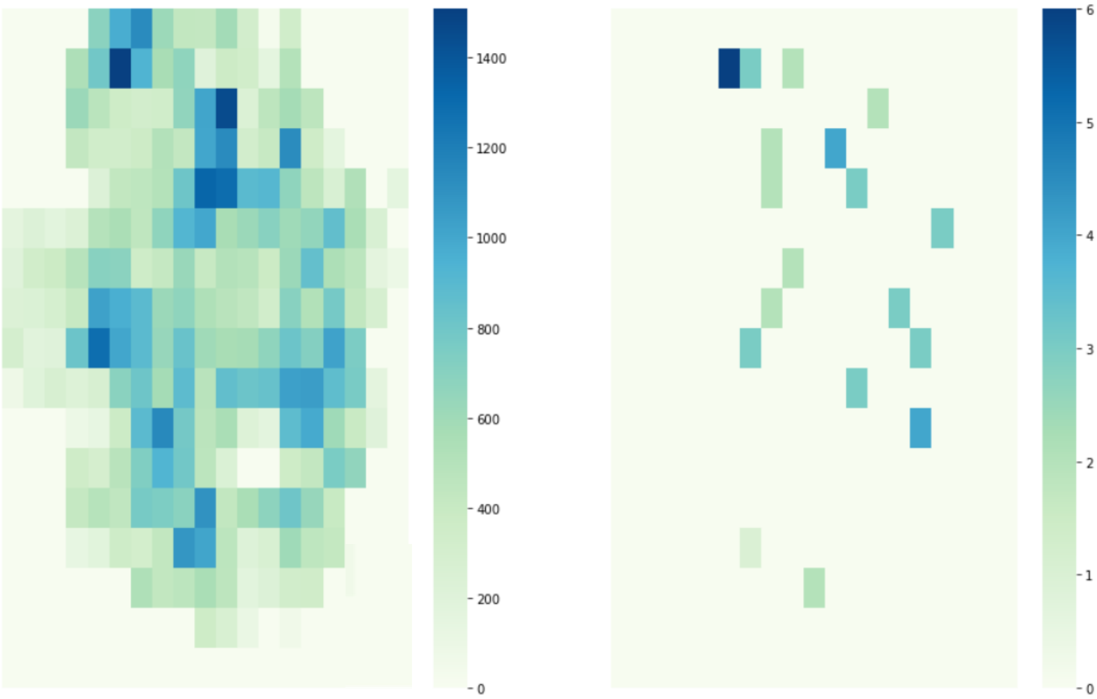


Figure 22 - Parking slot allocation compared to overall latent demand. Iteration #3

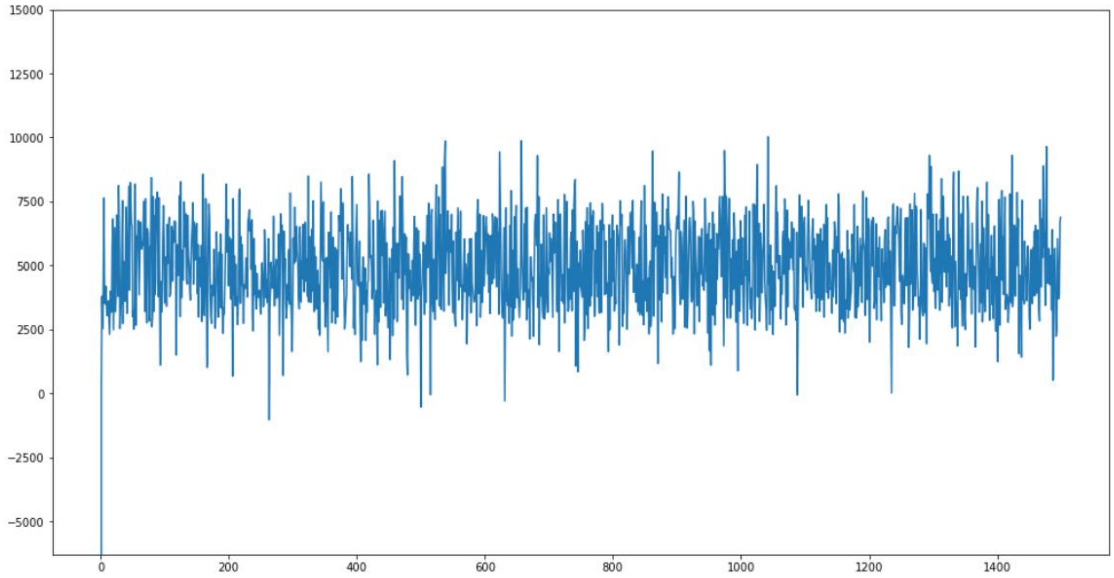


Figure 23 - Fitness function. Iteration #3

7.2.4. Fourth iteration

- The best fitness value obtained was found in iteration #1435 . The value reached was 10634.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 1 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 5 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 5 5 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 3 3 0 0 0 0 0 0 0]
 [0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0]
 [0 0 0 0 6 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 15 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

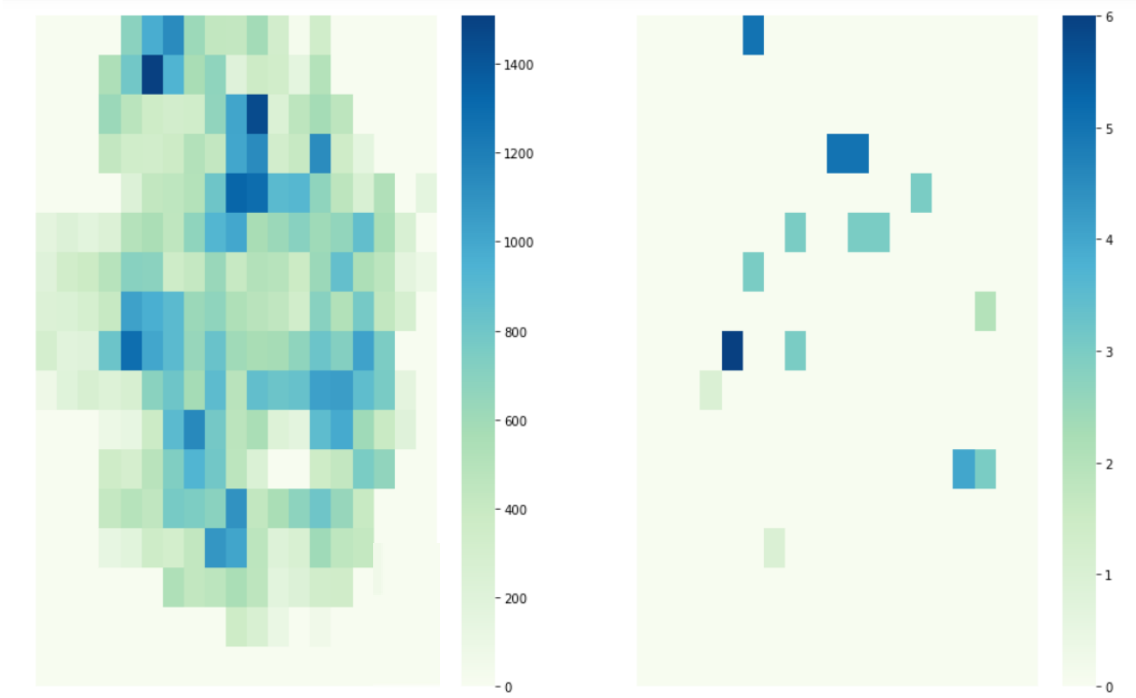


Figure 24 - Parking slot allocation compared to overall latent demand. Iteration #4

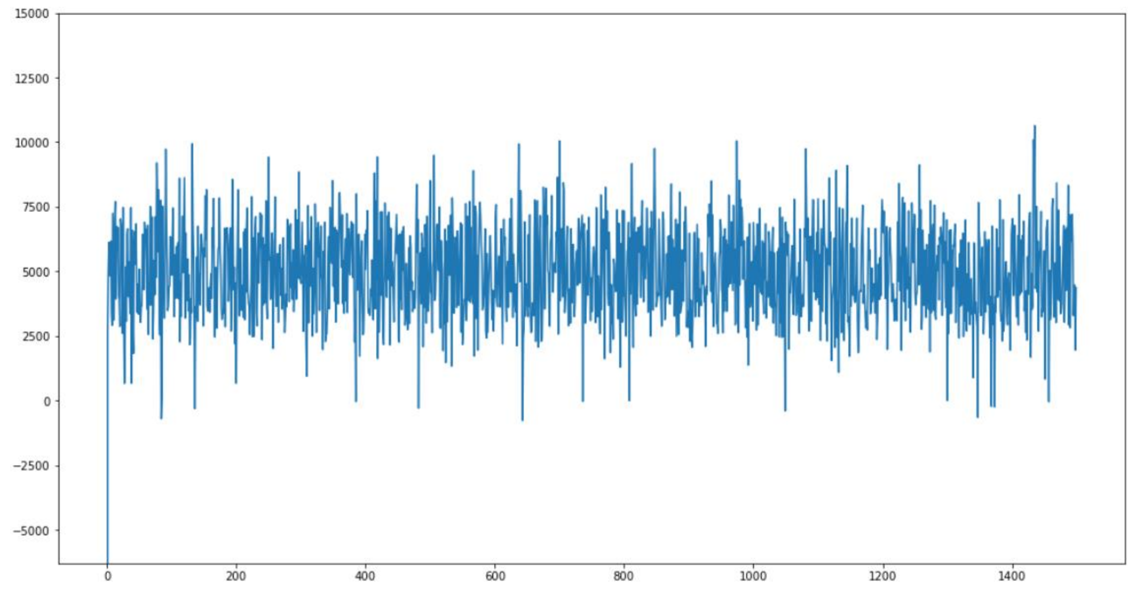


Figure 25 - Fitness function. Iteration #4

7.2.5. Fifth iteration

- The best fitness value obtained was found in iteration #376. The value reached was 11752.
- The best individual found in the whole algorithm was the following:

Best individual:

or parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 6 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 2 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 0 0 0 0 0 0]
 [0 0 0 0 0 3 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 3 0 0 0 1 3 0 0 0 0 0]
 [0 0 0 0 0 0 4 3 0 0 0 0 0 0 3 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0]
 [0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 2 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 6 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 0 0 0 2 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 0 0 0 0 0 0]
 [0 0 0 0 0 3 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 3 0 0 0 1 3 0 0 0 0 0]
 [0 0 0 0 0 0 4 3 0 0 0 0 0 0 3 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0]
 [0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 2 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 19 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

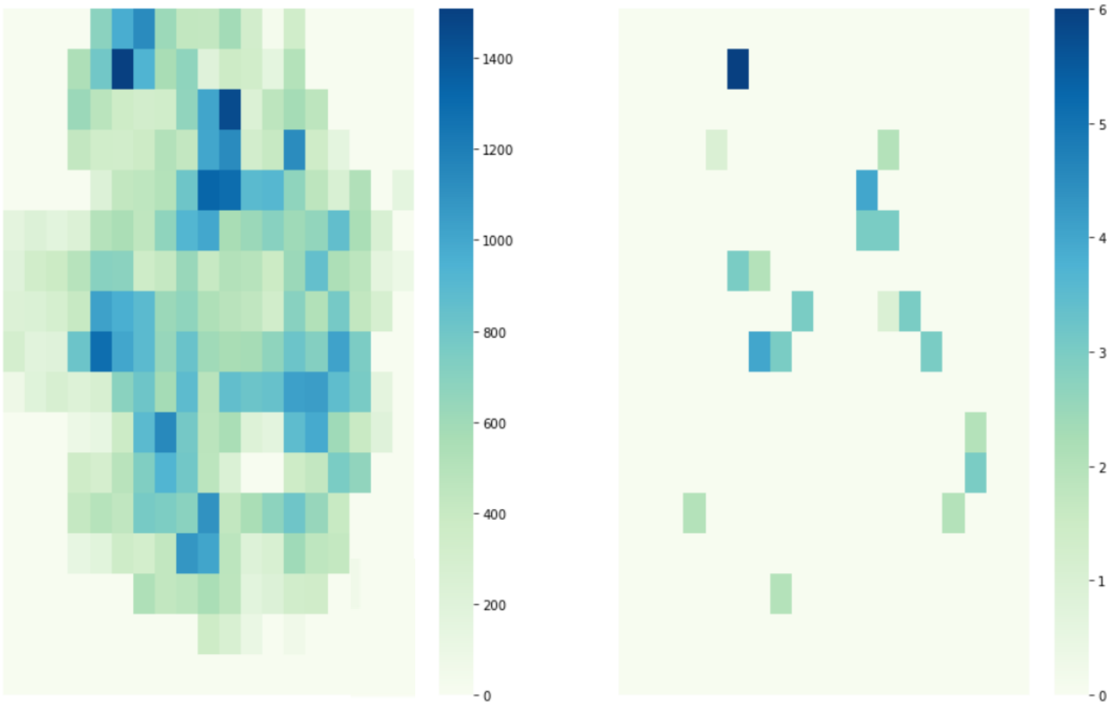


Figure 26 - Parking slot allocation compared to overall latent demand. Iteration #5

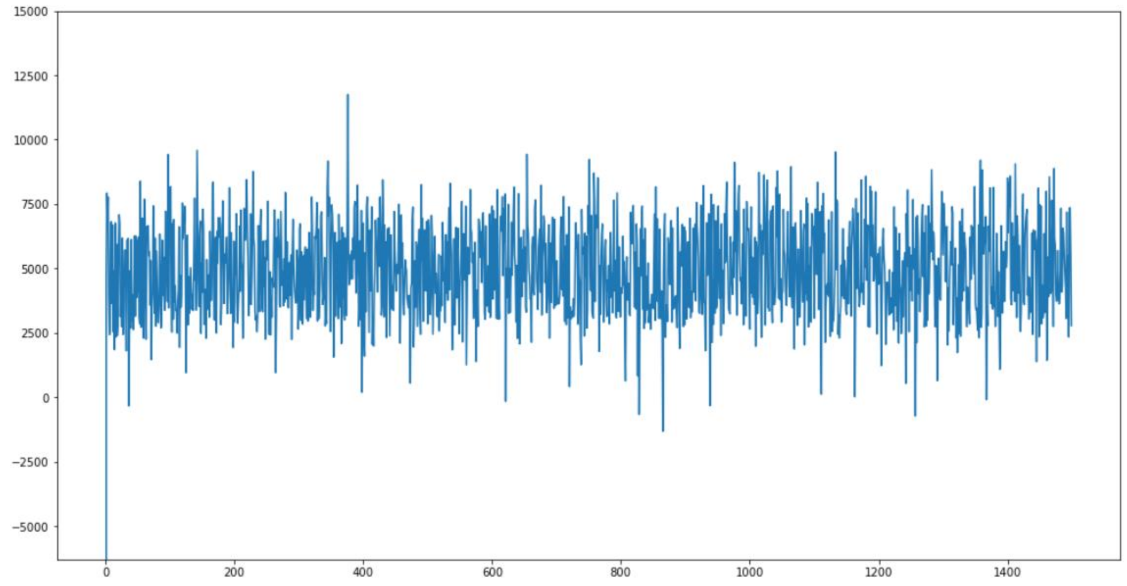


Figure 27 - Fitness function. Iteration #5

7.2.6. 6Th iteration

- The best fitness value obtained was found in iteration #1353. The value reached was 10720.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 1 1 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 4 0 0 0 0 2 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 2 0 0 0 0 0 5 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 4 0 0 0]
[0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 6 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 2 0 0 0 0 0 0 0 4 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 5 2 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 15 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

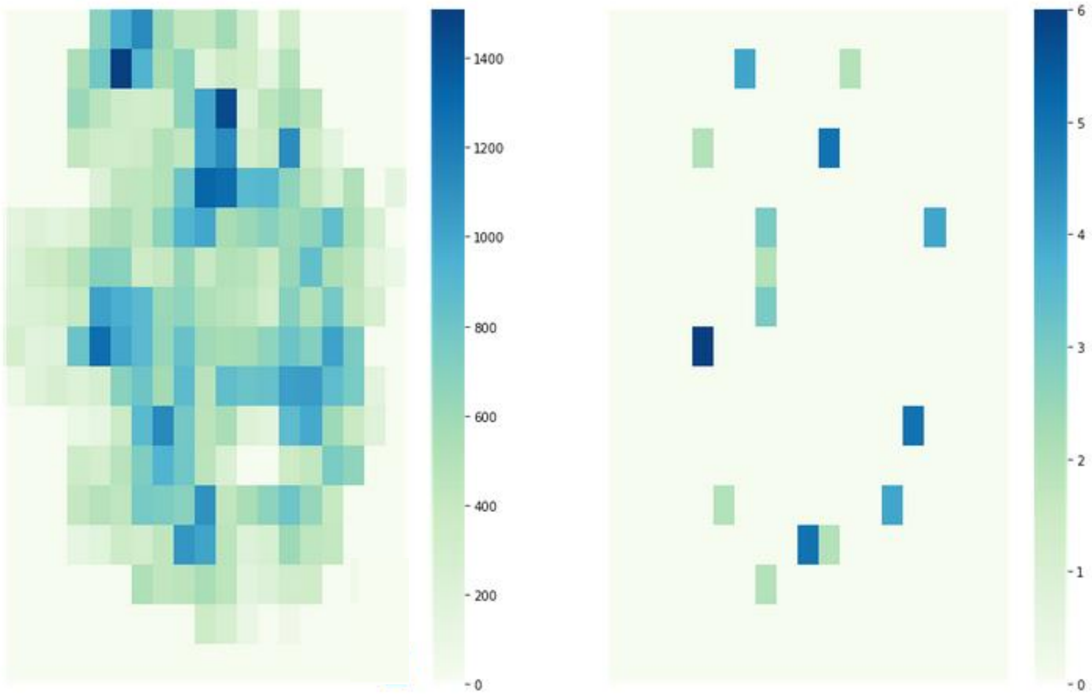


Figure 28 - Parking slot allocation compared to overall latent demand. Iteration #6

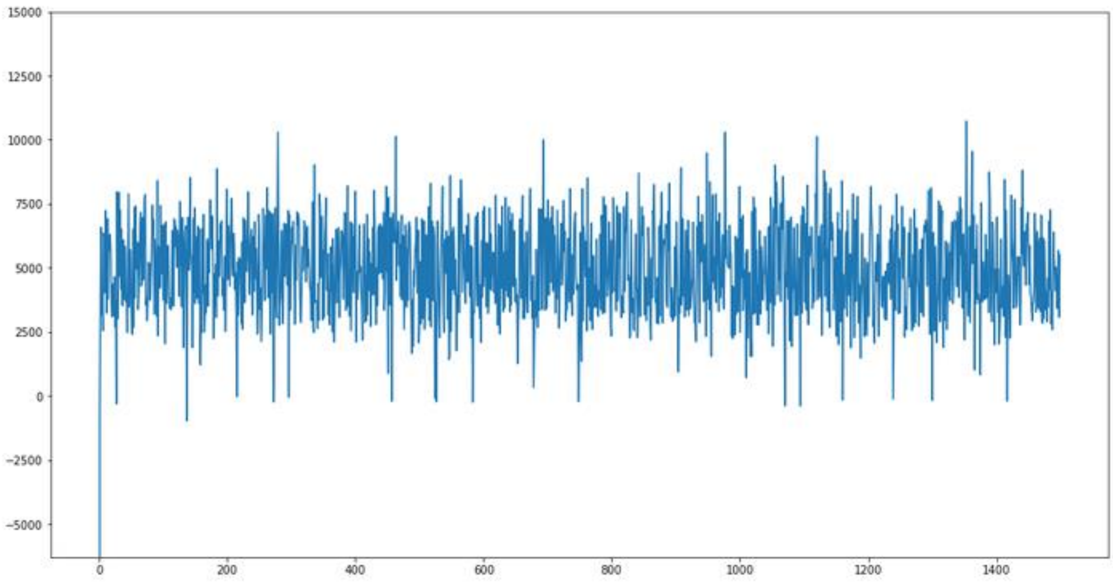


Figure 29 - Fitness function. Iteration #6

7.2.7. 7th Iteration

- The best fitness value obtained was found in iteration #812. The value reached was 9764.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 8 5 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 2 0 0 0 0 5 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0]
 [0 0 0 0 0 0 2 0 0 0 3 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 2 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 4 0 0 0]
 [0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 15 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

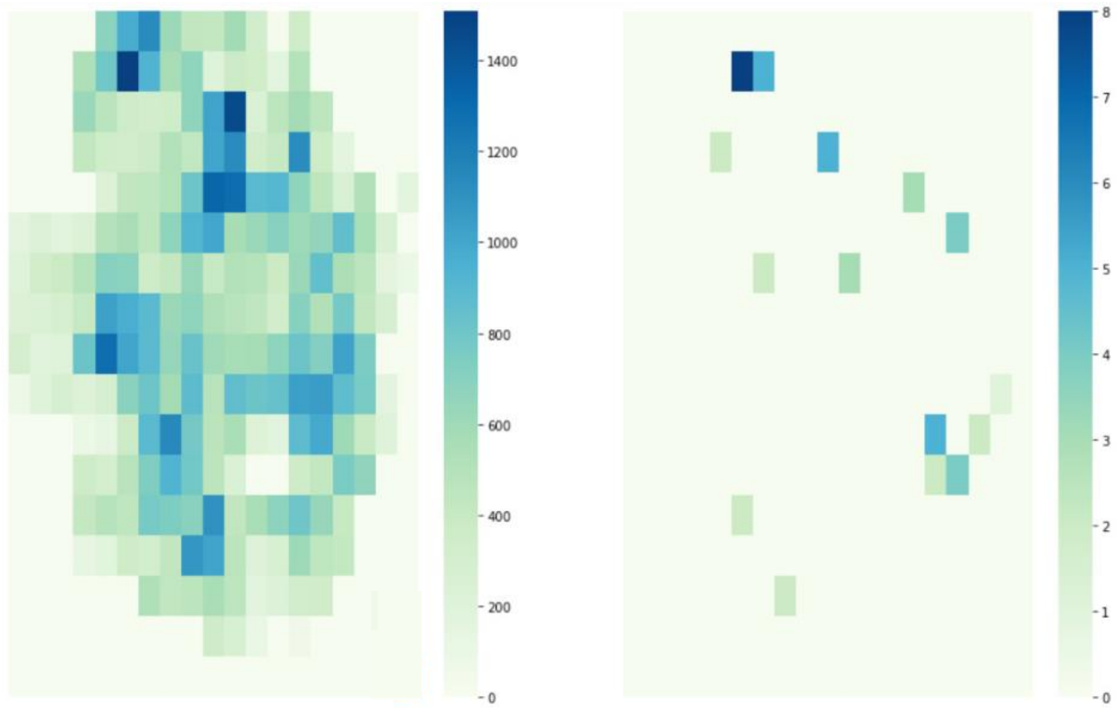


Figure 30 - Parking slot allocation compared to overall latent demand. Iteration #7

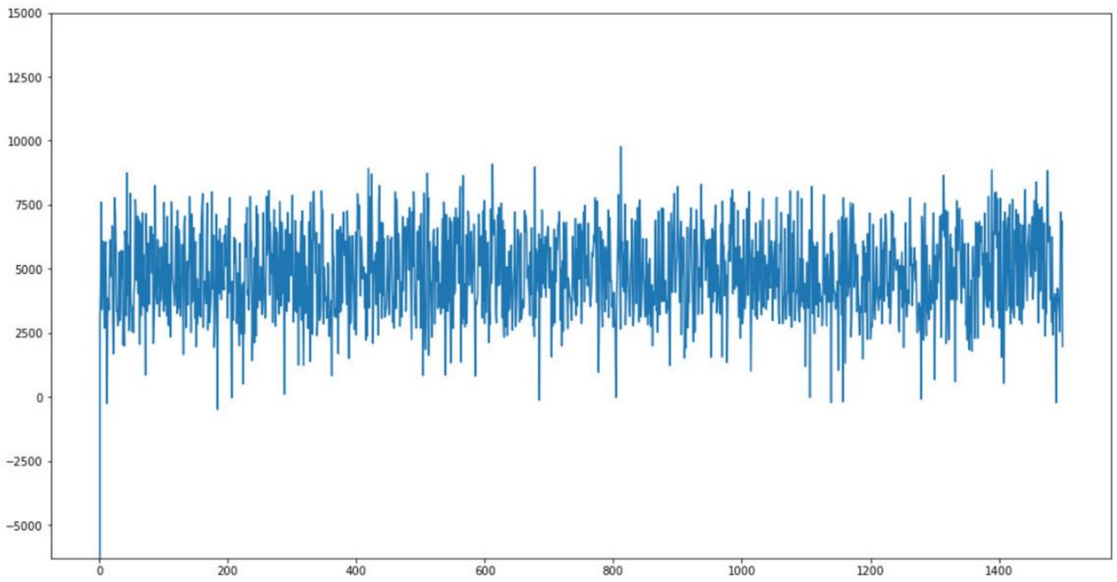


Figure 31 - Fitness function. Iteration #7

7.2.8. 8th Iteration

- The best fitness value obtained was found in iteration #867. The value reached was 9930.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 1 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 5 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 5 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 2 0 0 5 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 0 5 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0]
 [0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 13 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

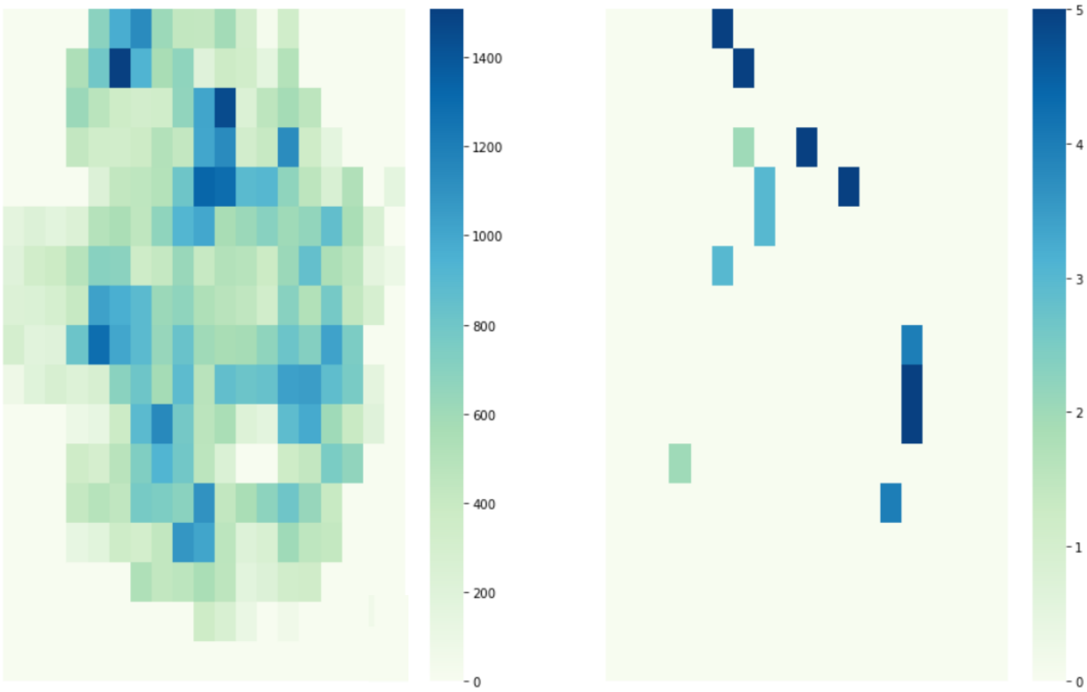


Figure 32 - Parking slot allocation compared to overall latent demand. Iteration #8

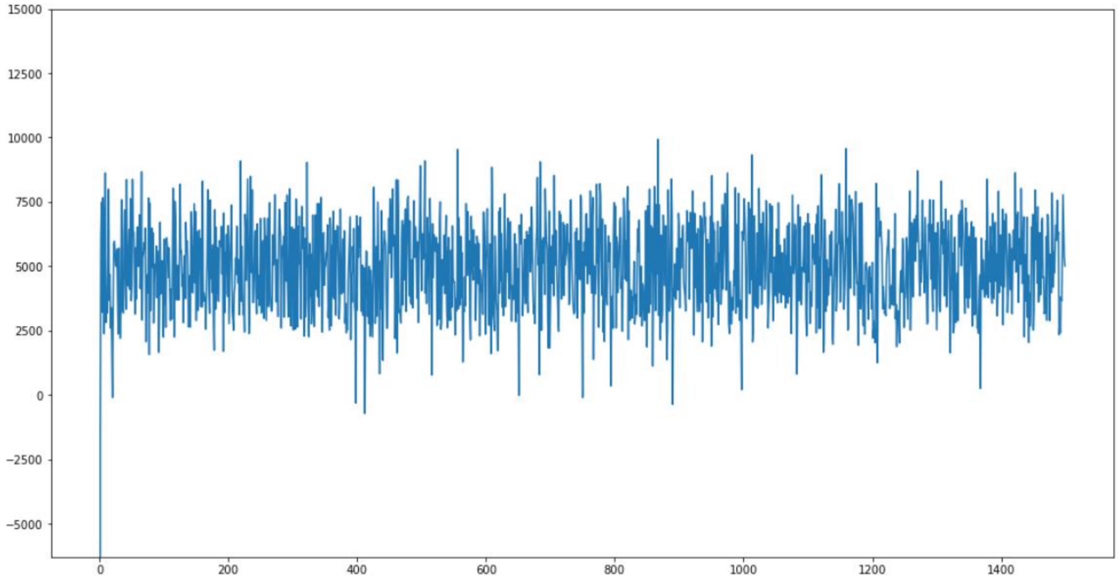


Figure 33 - Fitness function. Iteration #8

7.2.9. 9th iteration

- The best fitness value obtained was found in iteration #1450. The value reached was 10976.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 0 0 0]
[0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 1 0 1 0 0 0 0 0 0 0]
[0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
[0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 5 0 0 2 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0 0]
[0 0 0 0 0 0 0 3 0 0 0 0 3 0 0 0 0 0 0]
[0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 2 0 2 0 0 0 0 0 0 0]
[0 0 0 0 6 0 0 0 0 0 0 0 0 0 3 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0]
[0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 2 0 0 0 0 0 0 0 4 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 5 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 16 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

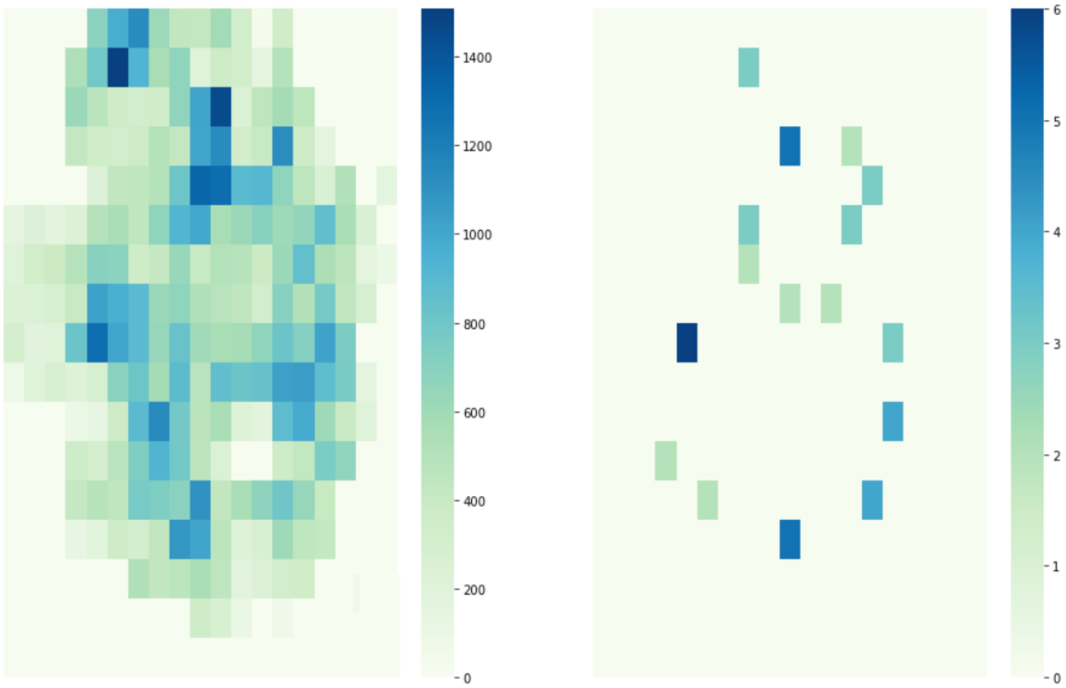


Figure 34 - Parking slot allocation compared to overall latent demand. Iteration #9

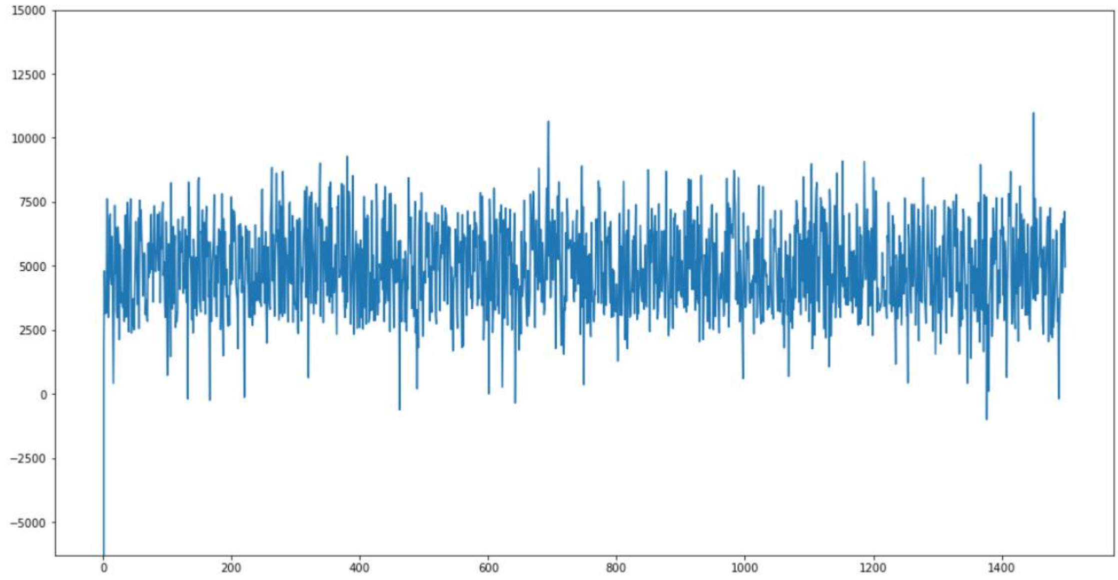


Figure 35 - Fitness function. Iteration #9

7.2.10. 10th iteration

- The best fitness value obtained was found in iteration #1448. The value reached was 9601.
- The best individual found in the whole algorithm was the following:

Best individual:

```
[[0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 1 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0]
 [0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

Number of parking slots per parking:

```
[[0 0 0 0 0 5 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 7 0 5 0 0 0 0 0 0 0 0 0 4 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 5 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 4 0 0 0]
 [0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

- A total of 12 parking stations where taken into consideration.
- Parking slot allocation has been distributed as follows:

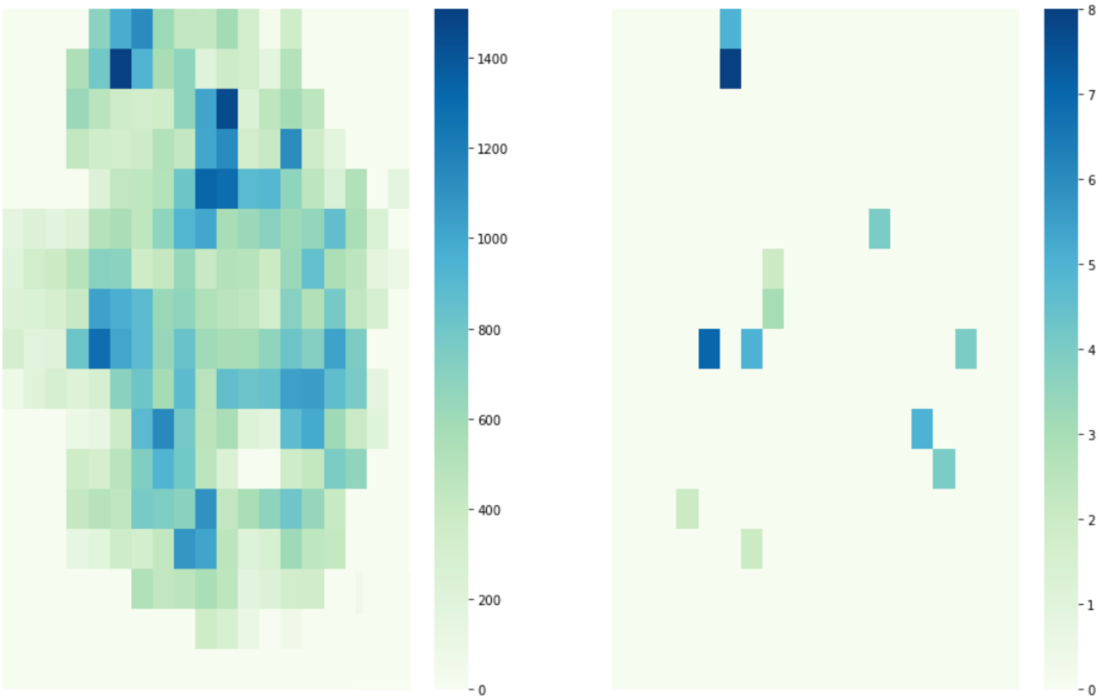


Figure 36 - Parking slot allocation compared to overall latent demand. Iteration #10

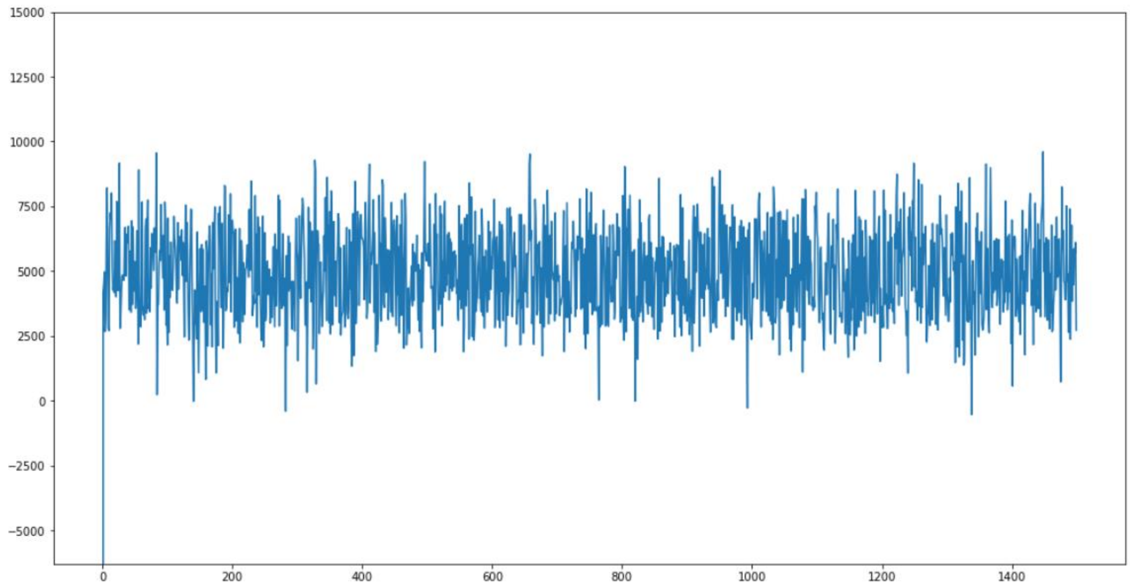


Figure 37 - Fitness function. Iteration #10

7.3. CODE

7.3.1. GENERATION OF MESH

```
import geopandas as gpd
from shapely.geometry import Polygon
import shapely
import ast
from geopandas import GeoDataFrame
from geomet import wkt
import json
import geopandas as gpd
import folium
import matplotlib.pyplot as plt

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import plotly.express as px
import shapefile as shp
import seaborn as sns
import os
from matplotlib import transforms

map = folium.Map(location = [40.48,-3.7], tiles='cartodbpositron' ,
zoom_start = 10.5)

df =
gpd.read_file(r'C:\Users\bvela\OneDrive\Escritorio\ICAI_MASTER\TFM\DAT
OS_ALEJANDRO\GRID_Coordinates.csv')

df["geojson"] = df["Coordinates"].apply(lambda x:
json.dumps(wkt.loads(x)))
print(df.head())

df.crs = "EPSG:4326"
print(df.crs)

for _, r in df.iterrows():
    # Without simplifying the representation of each borough,
    # the map might not be displayed
    geo_j = r['geojson']
    style = {'fillColor': 'lightblue', 'color': 'blue'}
    geo_j = folium.GeoJson(data=geo_j,style_function=lambda x: style)
    geo_j.add_to(map)

df_parkings =
pd.read_excel(r"C:\Users\bvela\OneDrive\Escritorio\ICAI_MASTER\TFM\APA
RCAMIENTOS\CoordenadasAparcamientos.xlsx")

for _, r in df_parkings.iterrows():
    lat = r['PARlatitud']
    lon = r['PARlongitud']
    if r['PARtipo']=='ROTACIÓN':
        folium.Marker(location=[lat, lon],popup={r['PARNombrePar'],
r['PARtipo']},icon=folium.Icon(color='red', icon='car',
prefix='fa')).add_to(map)
    elif r['PARtipo']=='MIXTO':
```

```
        folium.Marker(location=[lat, lon],popup={r['PARNombrePar'],
r['PARtipo']},icon=folium.Icon(color='darkblue', icon='car',
prefix='fa')).add_to(map)
    elif r['PARtipo']=='RESIDENTES':
        folium.Marker(location=[lat, lon],popup={r['PARNombrePar'],
r['PARtipo']},icon=folium.Icon(color='green', icon='car',
prefix='fa')).add_to(map)

map
```

(Plotting polygons with Folium — GeoPandas 0.10.2+0.g04d377f.dirty documentation, 2022)

(Muller, 2022)

7.3.2. GENETIC ALGORITHM

```
import geopandas as gpd
from shapely.geometry import Polygon
import shapely
import ast
from geopandas import GeoDataFrame
from geomet import wkt
import json
import geopandas as gpd
import folium
import matplotlib.pyplot as plt
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import plotly.express as px
import shapefile as shp
import seaborn as sns
import os
from matplotlib import transforms
import random as rand
import seaborn as sns
import array

n_iterations=1500
n_pop=600 #EVEN NUMBER
seleccion=2
r_cross=0.8
r_mut=0.05
t=1600 #tiempo medio que está un coche aparcado en un parking público
(anualmente)
ntot_plazas=50 #por ejemplo

demanda =
pd.read_excel(r'C:\Users\bvela\OneDrive\Escritorio\ICAI_MASTER\TFM\DAT
OS_ALEJANDRO\od everything.xlsx', sheet_name='latent_heatmap')
demanda.to_numpy()
demanda=np.array(demanda)


tarifas =
pd.read_excel(r'C:\Users\bvela\OneDrive\Escritorio\ICAI_MASTER\TFM\DAT
OS_ALEJANDRO\od everything.xlsx', sheet_name='tarifas')
tarifas.to_numpy()
```

```
tarifas=np.array(tarifas)
tarifas=tarifas*t

#matriz de parkings:
parking_publico=
pd.read_excel(r'C:\Users\bvela\OneDrive\Escritorio\ICAI_MASTER\TFM\DAT
OS_ALEJANDRO\od everything.xlsx',
sheet_name='loc_parking_demanda_nozero')
parking_publico.to_numpy()
parking_publico=np.array(parking_publico)

#GENERACIÓN DE LA POBLACIÓN
loc_parking=np.random.randint(0, 2, size=(n_pop, 17, 19))
loc_parking=loc_parking.astype(int)
loc_parking=np.array(loc_parking)

#FUNCIÓN CORREGIR POBLACIÓN
def corregir_poblacion(n_pop, parking_publico, poblacion):
    for i in range (n_pop):
        for j in range (17):
            for k in range (19):
                if(parking_publico[j,k]==0):
                    poblacion[i,j,k]=0
    return poblacion

#FUNCIÓN FITNESS
def fitness_value(individuo,demanda,tarifas):
    fitness=0
    for i in range (17):
        for j in range (19):
            if(individuo[i,j]!=0):
                fitness=fitness+demanda[i,j]-tarifas[i,j]

    #restricciones
    #contar numero de 1 en la poblacion con mejor fitness
    numero_uno=0
    for a in range (17):
        for b in range (19):
            if(individuo[a,b]!=0):
                numero_uno=numero_uno+1
    #print('\nNumero de 1:\n',numero_unos)
    if(numero_uno<10):
        fitness=-10000000
    if(numero_uno>20):
        fitness=-10000000

    #restricciones con respecto al numero de plazas por parking
    return fitness

#FUNCIÓN ORDENAR FITNESS
def ordenar_fitness(n_pop,fitness):
    fitness_ordenado=np.zeros((n_pop,2))
    for k in range (n_pop):
        max_v=-100000000
        for i in range (n_pop):
            if(fitness[i,0] > max_v):
                max_v=fitness[i,0]
                max_v2=i
                j=i
```

```
                fitness_ordenado[k,0]=max_v
                fitness_ordenado[k,1]=j
        fitness[max_v2,0]=-10000000000
    x=fitness_ordenado[0,1]
    x=x.astype(int)
    fitness_ordenado=fitness_ordenado.astype(float)
    return fitness_ordenado,x

def tournament (fitness,n_pop):
    posicion=rand.randint(0,n_pop-1)
    posicion2=rand.randint(0,n_pop-1)
    while(posicion==posicion2):
        posicion2=rand.randint(0,n_pop-1)
    if(fitness[posicion,0]<fitness[posicion2,0]):
        return posicion2
    else:
        return posicion

#FUNCIÓN CROSSOVER
def single_point_crossover(A,B,x):
    A_new=np.zeros((17,19))
    B_new=np.zeros((17,19))
    for i in range (17):
        for j in range(19):
            if(j<x):
                A_new[i,j]=A[i,j]
                B_new[i,j]=B[i,j]
            else:
                A_new[i,j]=B[i,j]
                B_new[i,j]=A[i,j]

    return A_new,B_new

def multi_point_crossover(A,B,X):
    for i in X:
        A,B= single_point_crossover(A,B,i)
    return A,B

#MUTATION
def mutation (A, r_mut):
    for i in range (17):
        for j in range (19):
            if rand.random()<r_mut:
                if(A[i,j]==0):
                    A[i,j]=1;
                else:
                    A[i,j]=0
    return A

mejor_cromosoma=np.zeros((n_iterations,17,19))
mejor_cromosoma_fitness=np.zeros((n_iterations,1))

for z in range (n_iterations):

    loc_parking=corregir_poblacion(n_pop, parking_publico,
loc_parking)

    #Calcular fitness
    individuo=np.zeros((17,19))
```

```
fitness=np.zeros((n_pop,1))
for i in range (n_pop):
    individuo=loc_parking[i,:,:]
    fitness[i,0]=fitness_value(individuo,demanda,tarifas)
fitness=fitness.astype(float)


fitness_2=fitness
for i in range (n_pop):
    max_pop=np.max(fitness)


#Ordenar fitness
fitness_ordenado,max_v2=ordenar_fitness(n_pop,fitness_2)
fitness_ordenado=fitness_ordenado.astype(int)

#Mejor cromosoma en la población
for x in range (n_pop):
    if(fitness_ordenado[x,0]==0 & x!=n_pop):
        if (x==n_pop):
            max_v2=1
        else:
            max_v2=fitness_ordenado[x+1,1]

mejor_cromosoma[z]=loc_parking[max_v2]


#Vector demanda de la poblacion con mejor fitness
best_fitness=loc_parking[max_v2,:,:]
demanda_parking=np.zeros((17,19))
for j in range (17):
    for k in range (19):
        if(best_fitness[j,k]!=0):
            demanda_parking[j,k]=demanda[j,k]
        else:
            demanda_parking[j,k]=0


#contar numero de 1 en la poblacion con mejor fitness
numero_unos=0
for i in range (17):
    for j in range (19):
        if(demanda_parking[i,j]>0.0):
            numero_unos=numero_unos+1
#print('\nNumero de 1:\n',numero_unos)

demandas_ordenadas=np.zeros((numero_unos,1))
for k in range(numero_unos):
    max_d=0.0
    for i in range (17):
        for j in range (19)
```