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FORECASTING EXPECTED DEMAND FROM AUTOMOTIVE SERVICE SHOPS, USING SELF-ORGANIZING NEURAL NETWORKS "SOM", ON A PARALLEL COMPUTING PLATFORM "CUDA"

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A B S T R A C T

This paper presents an unsupervised neural network schematic, on a parallel computing platform, for the prediction of expected demand from automotive service shops. Demand prediction is done by applying artificial neural networks of self-organized maps "SOM" and to optimize computing resources, parallel processing "CUDA" is applied. From the clusters generated by the network, the common characteristics of the vehicles that present a specific failure are identified, among the characteristics are, the mileage, the time without a visit to the workshop, average visits to the workshop, vehicle model, year of the vehicle, average mileage between each visit, number of maintenance performed, number of reported failures and time of seniority as an after-sales customer. In the training of the network, data obtained from the extraction of information from 60 Hyundai brand dealerships was used. Subsequently, new experimental data were added to the network to validate the proposal. Finally, it is demonstrated that the use of self-organized neural networks manages to generate the "Clusters" that allow predicting the expected demand regarding the type of failures that will occur in the vehicles that will inform the service workshops. Likewise, the processing time was optimized through the use of the parallel computing platform "CUDA".

1. INTRODUCTION

The Automotive Industry has a high economic, political and social impact, either locally or regionally, and it is enough to analyze some very simple examples of how this industry impacts human activity in the different areas of daily life. It is necessary to transport goods, products, people and for Mexico, land transport is one of the driving forces of its most important economy (Garcia-Remigio et al., 2020).

After-sales service should be assimilated by everyone at the automotive dealership as a competitive strategy. Knowledge of the customer, service history of their vehicles, as well as the relationship that exists with customers (Customer Relationship Management), creates

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a positive flow between customer and brand, and of course generates a long-term business. WORLD-CLASS COMPANY = EXCELLENT PRODUCT + EXCELLENT SERVICE (Sandoval Precht, 2019; Ruiz Vintimilla, 2024).

It is noteworthy that over 52% of customers renew their purchase with a brand, even if they acknowledge that the product purchased did not meet their expectations regarding its quality, but the service they received during the product's lifespan was very good. Conversely, only 36% of customers who purchase a high-quality product renew their purchase if the service received did not meet their expectations (Sánchez et al., 2007).

All authorized dealerships have a formal management system, a Dealer Management System (DMS), which records information about each vehicle visit. They also have a digital platform where all work performed on each vehicle is recorded, generating a large database with the service center's historical information. This system allows automotive workshops to calculate demand, which refers to the number of vehicles expected to visit the service center during a given period. Therefore, it is crucial to distinguish the vehicle type, year, and mileage, as these factors will determine the types of parts and services required.

Depending on the mileage, different types of vehicle needs may be derived, in addition to the maintenance service, which may demand different levels of technical specialization from the workshop technicians.

Once the expected demand has been calculated, it is also possible to estimate more precisely, the possible failures that the vehicles can generate, this is where Artificial Intelligence algorithms come in.

Demand Analysis: This involves applying queries to the database, based on statistical methods, to identify customer needs regarding the nature of their visits (Senabre et al., 2009). In other words, it allows for predicting the potential services that customers' vehicles will require during future visits, taking into account variables such as vehicle model, mileage, and year, among others.

This demand calculation must be considered when configuring the required capacity of the service workshop (Supply), based on customer service demand (Demand). The service workshop must be configured in terms of the number of service advisors and technicians required based on their specialization. This includes determining how many technicians are needed for maintenance, diagnostics, specialized mechanical work, and quality control, as well as the necessary production space, the quantity of spare parts in the warehouse, and specialized tools.

Capacity is generally defined as the maximum available production rate (Martinsa et al., 2017). However, capacity is often incorrectly defined without considering the time dimension. For example, some inaccurate measures of capacity are: the number of service advisors or productive ramps/bays.

The number of productive ramps/bays in the workshop represents the size of the facilities, but it is not a measure of production. The number of technicians assigned to a productive bay must be combined with an estimate of the time a vehicle spends in the workshop to arrive at a measure of capacity, such as the number of vehicles serviced per day, taking into account the service provided, i.e., whether it came for mileage service, diagnostics, or major repairs.

The concepts of capacity and volume are often confused.

Volume is the actual production rate in a unit of time; while capacity is the maximum production rate.

There are two types of capacity:

RECEIVING CAPACITY. This depends on the number of advisors and the time allocated to each vehicle. It is estimated that each advisor should not receive more than 12 vehicles in order to carry out the reception, tracking, and delivery process properly. This capacity should not be used as the basis for determining the number of vehicles that can be serviced in a day.

PRODUCTION CAPACITY. This is the number of vehicles that can be serviced in a day, taking into account the type of service provided (maintenance, diagnostics, and repairs). This capacity should be used as the basis for determining the number of vehicles that can be serviced by appointment in a day.

The type of failures this work focuses on are so-called "complex failures." These are failures that are not immediately apparent and typically require an analytical approach, generally including data collection and the identification of failure patterns. Most of these "complex failures" tend to involve interconnected vehicle systems, which contributes to their complexity and results in damage to more than one vehicle component (Pastor Flores et al., 2019).

Finally, the work considers the challenges related to the efficiency of vehicle repair service processes. These processes involve assessing the vehicle's condition and the information provided by the customer regarding the observed faults. Subsequently, the technician is responsible for diagnosing the fault based on their experience and the information gathered during the inspection.

Therefore, the diagnosis is based on the experience and expertise of the technician to detect the main failure and those that are derived from it, so proposing an Artificial Intelligence that allows a more accurate diagnosis could help to plan the correct time that the technician should take, which will completely eliminate, delays in delivery times and re-work caused by poor diagnoses, increasing the efficiency of the technician between 100% and 110%. (Bossio et al., 2017).

A general review of AI-based electrical machine fault diagnosis of unsupervised SOM neural networks is presented in (Kalteh et al., 2008). In techniques based on the use of Artificial Neural Networks (ANN), we will concentrate on Unsupervised Neural Networks (UNN), and mainly on Self-Organizing Maps (SOM) networks (Kalteh et al., 2008; Miljković, 2017). These networks have advantages for the generation of "Clusters" or groups of entities with respect to perceptron type networks. Especially, because it does not require having the training or fundamental database classified. In (Tosida et al., 2017) the cluster model is developed to uncover clusters of telecommunications companies that have influence on the national economy to make it easier for the government to supervise telecommunications companies.

Meanwhile (de Andrade et al., 2014) is to use the Self-Organized Map (SOM) to group the distributors with similar environmental variables of the concession areas and subsequently, evaluate the efficiency of the distributors, through the same first-stage DEA model carried out by ANEEL. Usually, classification techniques in AI are carried out from classes previously fed by pre-processing the input data.

Especially, in the diagnosis of faults in electrical machines, they use voltage and current measurements, using techniques such as the Motor Current Signature Analysis (MCSA), or instantaneous active and reactive powers, among others (Bossio et al., 2010). In Bossio et al. (2010) a technique to diagnose faults caused by mechanical imbalance and misalignment between the motor shafts and the driven load was shown, through the application of a self-organizing network (SOM). In another context, but trying to, (Martinelli et al., 2006) shows the usefulness of the application of SOM in the process of discovering patterns of identifying website usage habits, studying the necessary transformations to be made in the data of the access logs of the web servers to use them as input signals of the neural network. Then, the patterns discovered will be analyzed in order to understand and explain them.

In this work, different input variables are incorporated, such as mileage, time without a visit to the workshop, average visits to the workshop, vehicle model, year of the vehicle, average mileage between each visit, number of maintenance performed, number of reported failures and time of seniority as an after-sales customer, and through the efficient combination of the design of the SOM network, it is possible to generate the necessary "Clusters" for the prediction of the input demand, managing to isolate the failures that were identified in each of these "Cluters". It also allows establishing a threshold associated with the severity of the failures (Mendez-Monroy et al., 2009).

The training of the network was carried out using data extracted from the concentrated database regarding the history of visits of vehicles to Hyundai service workshops, at least 4 years old, with the aim of being able to be used later in an automatic diagnosis based on data obtained from the new entries that were made.

2. METHODOLOGY

As mentioned, the present work seeks to create a software that allows determining the expected demand of vehicles in service workshops, through the use of an artificial neural network of the type of self-organizing maps and to optimize the computing resources, the parallel processing "CUDA" is applied. To achieve this objective, it is necessary to carry out a series of activities that can be grouped into 5 blocks that are shown in Figure 1, and which are described below.

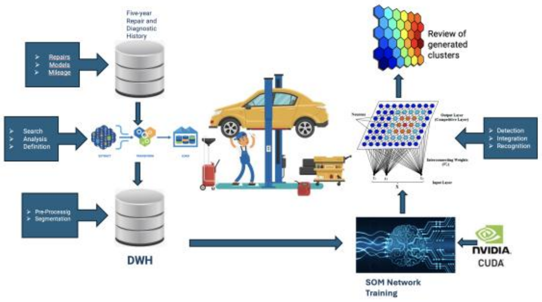

Figure 1. General diagram of the methodology used for the research.

Figure 1 illustrates the overall process of the proposed platform. The first step involves collecting, cleaning, organizing, and storing historical data on services, diagnoses, and repairs performed on vehicles that visited after-sales workshops. This data will then be analyzed using Artificial Intelligence (AI) algorithms. This analysis will also allow for the calculation of expected demand in terms of vehicle arrivals and service characteristics, as well as the detection of complex failure patterns. Furthermore, AI algorithms will enable the prediction of future failures. To achieve these objectives, Artificial Neural Networks (ANNs) will be trained to analyze and process the stored information, which for the purpose of this article is the application of SOM networks.

2.1 Database

The first stage consists of integrating a robust database with information from at least 60 dealerships, containing historical workshop visits, service orders for at least the last 5 years, as well as repair and diagnostic records (Perrin Pereiro, 2022).

2.2 Standardization

Following the ETCL process, the information is grouped using the "Snowflake" model data warehouse methodology, normalizing the database into fact entities and dimensions.

Figure 2 shows the architecture that was developed for the extraction of information from the dealerships.

A REST API was developed to extract data from dealerships and centralize it on the analytics service's server. HTTPS protocols were used to provide the security certificate (.crt and .key files) linked to each dealership's domain.

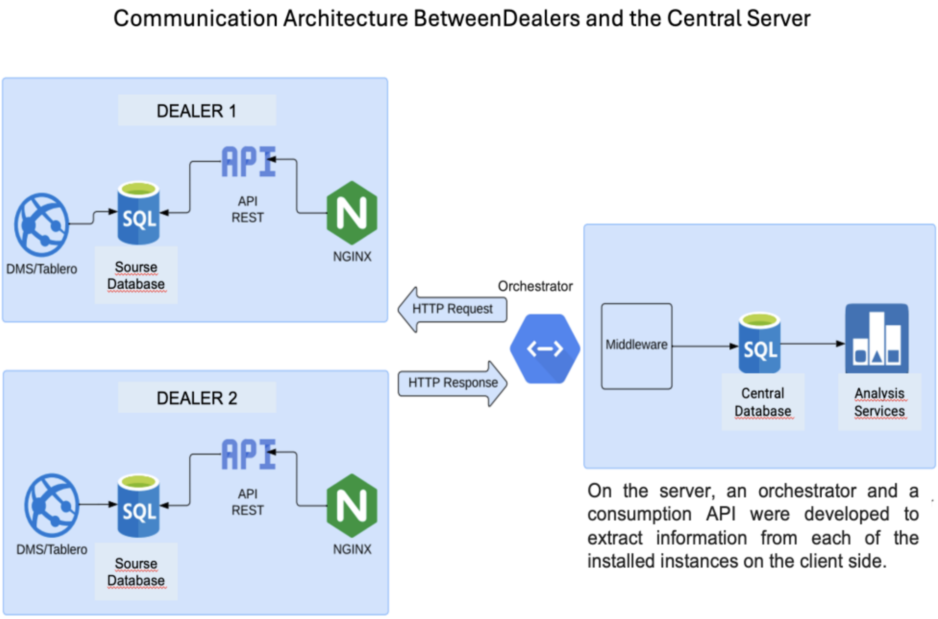

Figure 2. Communication architecture between dealers and central server

This API only allows queries from the central server's public address and rejects requests from other sources.

Using algorithms in the "MS SQL Server" database information processing programming language (Structured Query Language), the information was organized in such a way as to generate the input variables for the input neurons of the SOM NETWORK, which were the following:

CHARACTERISTICS

- Type of Operation Analysis
- Mileage
- Number of Maintenance Services
- Number of Repairs
- Number of Diagnostics
- Time Since Last Visit
- State of the Republic

2.3 Training

The selected variables are used as input for the "SOM" neural network that allows the identification of "Clusters" and in this way the calculation of the expected demand of the vehicles that will enter the workshop. For this phase it was necessary to consider parallel programming to minimize the computational costs of training, so a GPU with CUDA is used for its implementation (Szlifierz Criado, 2023).

Experimental trainings were carried out, in order to use the selected variables to build and train the "SOM" network. These tests corresponded to the use of information cases corresponding to 10 concessionaires. Network validation was subsequently performed using new information from 10 other different dealerships. Finally, the information of the 60 concessionaires was used.

3. RESULTS SELF-ORGANIZED MAPS

The research presented in this work is based on the implementation and use of SOM type networks, originally proposed by "Teuvo Kohonen" (Carpio Martin, 2020). These networks are based on simulating in one way, the ability of the human brain to generate topological maps from signals perceived from the outside. These networks are of the type known as competitive unsupervised learning, since they do not seek to generate an objective output where it should tend, that is, there is no class or result that indicates whether the network is working correctly or incorrectly.

3.1 Architecture of Self-Organizing Networks "SOM"

A SOM network is composed of two neural layers, which are called input layers (composed of *N* neurons, one for each input variable), and output layer (formed by *M* neurons). The first layer is responsible for receiving and transmitting the information to the output layer. In the end, the output layer is responsible for processing the information received, as well as building the map of information or grouped data. The connection and flow between the two layers that make up the network is always *feed-forward*, causing information to propagate from the input layer to the output layer, where each input neuron *i* is connected to each output neuron *j* through the wij weights (Garcia Ruiz, 2014).

Therefore, the output neurons have an associated vector *w j* called the reference vector (codebook), thus establishing the average vector of the category represented by the output neuron *j*. In this way, the network defines a projection from a high-dimensional data space to a two-dimensional map as shown in Figure 3.

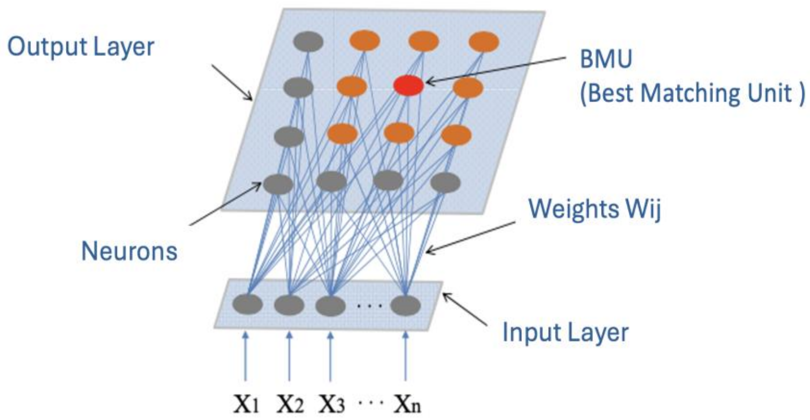

Figure 3. Architecture of Self-Organizing Networks "SOM".

3.2 Self-Organizing Networks Algorithm "SOM"

The SOM network learning process is carried out through the following steps:

The first step is to select a dataset, a random vector *x*, and proceed to calculate the distance (similarity) towards the vectors of the *codebook*, using the Euclidean distance method:

$$\|x - w_c\| = \min_j \left\{ \|x - w_j\| \right\}$$

Where *c* is the neuron whose weight is closest to the input vector.

After finding the nearest vector, named as BMU (*Best Matching Unit*), the remaining vectors of the codebook are updated. The magnitude of attraction between the BMU and its adjacent vicinity to vector *x* in the data space is governed by the α learning rate. This rate gradually decreases to zero, as well as the neighborhood radius, through the process of updating and assigning new vectors to the map.

The update of the reference vector given *i* is done by the rule shown, as well as it should be noted that the number of training steps must be previously fixed.

Rule 2.

$$w_j(t+1) = \begin{cases} w_j(t) + \alpha(t)(x(t) - w_j(t)) & j \in N_c(t) \\ w_j(t) & j \notin N_c(t) \end{cases}$$

After the training of the network is completed, it proceeds to form the topological map, in other words, the *n* topologically close vectors are applied, in the *n* contiguous neurons or even, in the particular case, within the same neuron.

3.3 Viewing a SOM Network

The most commonly used method to present the results in a SOM network is through the unified distance matrix, or heat map, which shows the resulting map as a regular mesh of neurons, where each element corresponds to a neuron. By generating the U matrix, a distance matrix is calculated between the reference vectors of contiguous neurons on the two-dimensional map. Finally, a type of graphic representation is selected through the use of colors or grayscales, so that the distance between two neurons will be shorter the darker the color between them.

Finally, algorithms were developed in the MS SQL Server database information processing programming language (Structured Query Language), which were used to organize the information in such a way as to generate the input variables for the SOM network's input neurons. These variables were as follows Model, year_model, Type Operation Analysis, Type operation, mileage, quantity of maintenances, quantity of repairs, quantity of Diagnoses and time without_ visit.

The hyperparameters used were:

- Network size: Defines the number of neurons in the network or the number of cells the mesh will contain: 5 x 5
- Learning rate: Controls how quickly the neuron weights adjust during training. It usually decreases over time: 0.3
- Neighborhood radius: Determines the extent of a neuron's influence on its neighbors during the training process. This value can also decrease over time.
- Number of iterations or epochs: Specifies how many times the entire dataset will be processed during training: 400
- Neighborhood function: Defines how the influence of neighboring neurons decays: Gaussian
- Weight initialization: Method used to establish the initial weights of the neurons before starting training: Random between 0 and 1

The SOM networks were programmed in Python using information organized in an SQL database table. Each variable was converted into an input neuron of the SOM model, to which the State of the Republic trait was added.

As a result, the following heat maps were generated, showing the resulting clusters. The grid was configured as 5 x 5. A heat map was generated for each model, for example the following figure (Figure 4).

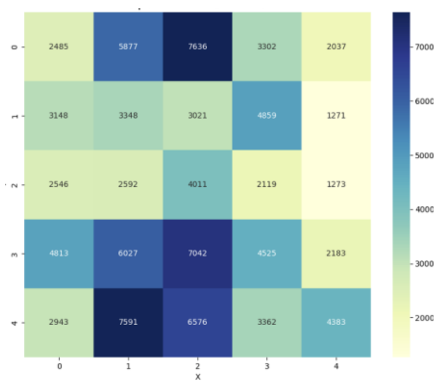

Figure 4. Example of a Heat Map model TUCSON.

The next graph (Figure 5) shows the clustering generated after processing in the SOM network. The most representative vehicle models are the CRETA, ELANTRA, GRAND I10, ACCENT and TUCSON. For the purposes of this article, the analysis of the processing results will focus on the TUCSON model.

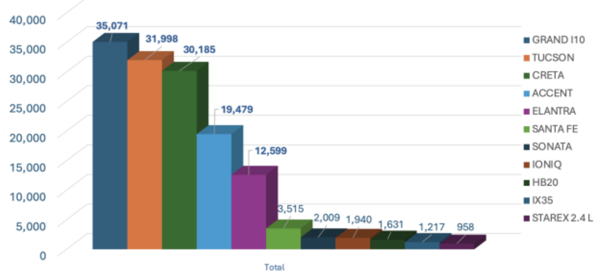

Figure 5. Most representative model

The following graph (figure 6) shows the model that accounts for the most repairs.

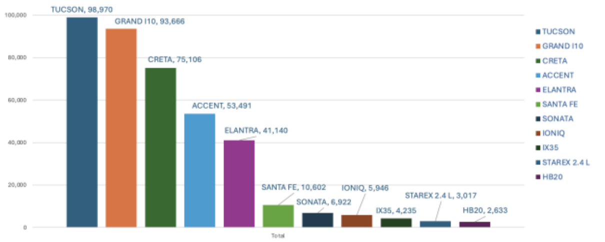

Figure 6. Most representative model-repairs

The graph shows that Tucson is the model that accounts for the most repairs after the SOM network processing.

The following graph (Figure 7) shows the number of repairs per average by vehicle type

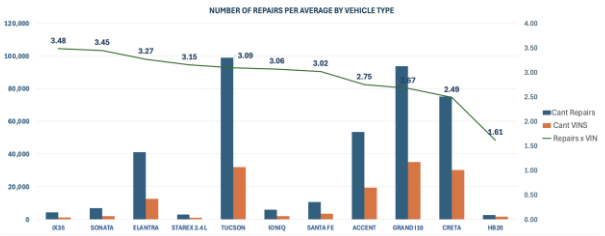

Figure 7. Number of repairs per average by vehicle type

Analyzing graph 7, it is shown that the IX35 model has the highest average number of repairs, while the HB20 model has the lowest. The average number of repairs for all models is 2.91, with the TUCSON model being above the average at 3.09 repairs per vehicle, making it the model with the most repairs overall.

The graph (Figure 8) shown below represents the average number of repairs per model, showing the price of the model.

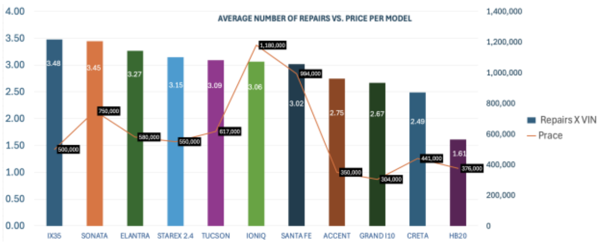

Figure 8. Average number of repairs vs. Price per model

The most expensive model is the IONIQ, priced at $1,180,000 MXN. This model is more cost-effective, given its price, as it only requires an average of 3.06 repairs per vehicle. The average price is $603,000 MXN, and the TUCSON model is slightly above the average, with 3.09 repairs per vehicle, making it a profitable model. The SONATA model is the least profitable, as it has the second-highest average number of repairs per vehicle and is also the second most expensive model in the Hyundai range analyzed in this article.

The following graph (Figure 9) shows the average repair cost based on the mileage of each vehicle. This graph includes only three models: Tucson, IONIQ, and GRAND i10, representing low-end, mid-range, and high-end models respectively, based on their price. The graph also includes the number of vehicles at each mileage level, reflecting the number of vehicles visiting the workshop at that mileage.

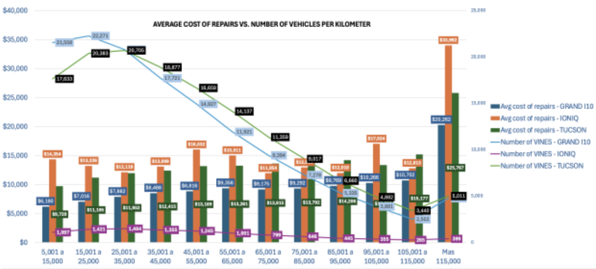

Figure 9. Average cost of repairs vs. Number of vehicles per kilometer

The last graph shows the decrease in the number of vehicles visiting the repair shop as mileage increases. This indicates that a higher number of vehicles visit the shop at the beginning of their service life, but this number decreases as mileage rises. Therefore, we can conclude that the number of vehicles in service at repair shops decreases with each additional mileage. The graph also shows that higher mileage leads to higher repair costs because the repairs required are more specialized and therefore more expensive. This same pattern is observed across all three vehicle models: a high number of service visits at the beginning of the service life, but this decreases over time as mileage increases. For example, in the TUCSON model, at mileages between 5,000 and 15,000, 17,633 vehicles visited the workshop and the average cost of repairs and maintenance was 9,729. In contrast, at mileages between 105,000 and 115,000, only 3,440 vehicles visited the service center, with an average cost of repairs and maintenance of 15,177. This meant an 80% decrease in vehicle visits to the service center, with a 40% increase in cost.

The following graph of model TUCSON, Figure 10 representative Clusters are generated, of which the most significant Clusters are 20,24 and 13.

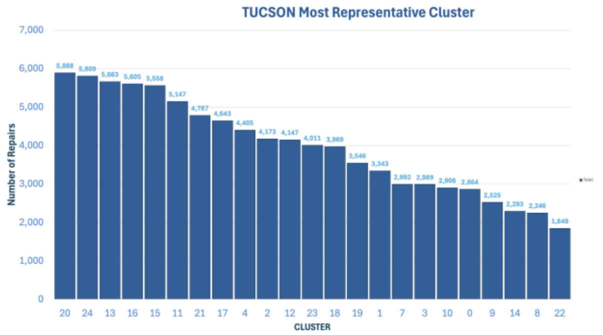

Figure 10. Cluster vs Model Tucson

The following Figure 11 shows the Mexican states that have the most repairs in the most representative clusters.

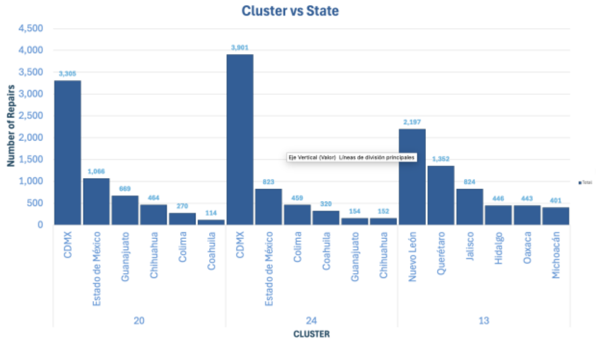

Figure 11. Cluster vs Model Tucson

As a result of processing on the SOM network and taking as a basis the most representative Clusters 20, 24 and 13 for the TUCSON model, the states of Mexico that grouped the most repairs were CDMX and Nuevo Leon.

The following graph Figure 12 shows the most common repairs, which were grouped in cluster 20. It also shows the Mexican state with the highest incidence of each of these repairs in the Tucson model.

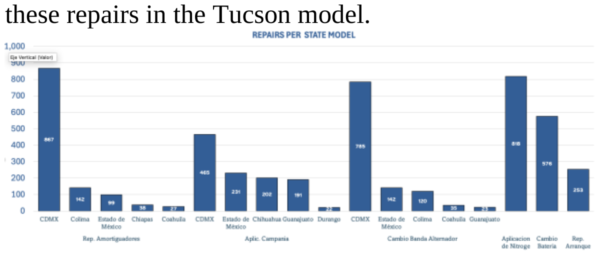

Figure 12. Repair vs State Model Tucson.

As shown in figure 12, the most common repairs grouped in cluster 20 are: shock absorber repairs, campaign applications, alternator belt replacement, nitrogen inflation, battery replacement, and starter repairs. The state with the highest number of these repairs is Mexico City (CDMX), followed by the State of Mexico and Colima.

The purpose of the following graph Figure 13 is to show which mileages are most representative in cluster 20 in Mexico City

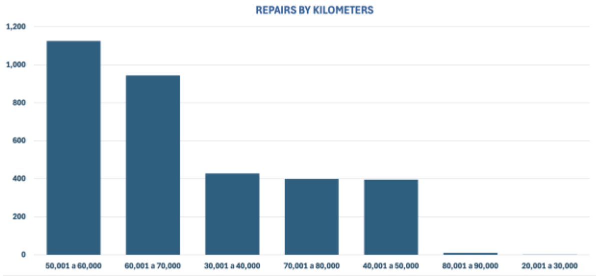

Figure 13. Repair vs Mileages Cluster 20 CDMX.

As shown in Figure 13, the most representative mileages grouped in Cluster 20 of the TUCSON model are vehicles with 50,000 to 60,000 KM, followed by 60,000 to 70,000. The next step is to analyze what repairs are found at these mileages in the CDMX.

The objective of the following graph Figure 14 is to show which repairs are most common at the most representative mileages, in cluster 20 of the Tucson model in Mexico City.

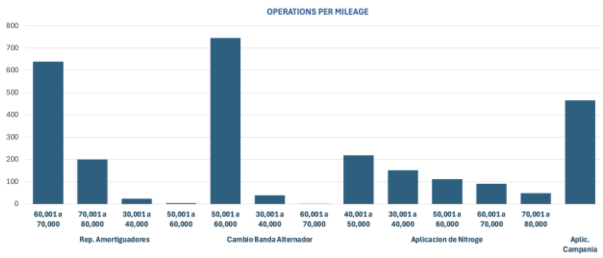

Figure 14. Repair vs Mileages Cluster 20 CDMX

As shown in Figure 14, the most common repairs are shock absorber repairs, alternator belt replacement, and nitrogen application, at the most representative mileages of 60,000 to 70,000 and 50,000 to 60,000 respectively.

Analyzing the results of the generated cluster 20, the operations contained in them are those shown in Figure 14, the most notable is Shok Absorber.

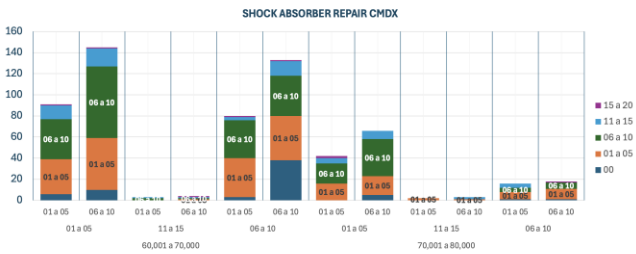

Figure 15. Cluster vs Operation Shok Absorber

In Figure 15, the result of the grouping of each Cluster is detailed, taking into account the Kilometers, number of maintenance operations, number of operations and time without visit, which are the input variables for training, resulting in the content of each cluster, which in the case of the graph, were selected as operations, for example, Shok Absorber.

For practical purposes, the operation, Shok Absorber, was selected, where it is concluded that when a vehicle TUCSON has between 60,000 and 70,000 kilometers traveled and has between 6 and 10 months without a visit with more than 5 maintenance operation and has between 1 and 10 general operation, it will be necessary to review this service operation.

4. CONCLUSIONS

The integration of information from the different concessionaires presented several challenges that were addressed to ensure a successful process and that the integrated data was accurate, consistent, and useful.
Some of the challenges encountered during the integration of information were:

Data quality: There was incomplete, incorrect, duplicate, or outdated data.
Data inconsistencies: The data came from different sources, were structured differently, and used different naming conventions, all of which were corrected.

Service-oriented management (SOM) helps identify patterns or segments within historical failure data. For example, it can group historical variables such as mileage, time since last service, vehicle model, number of previous repairs, and number of previous maintenance visits to detect trend patterns relevant to identifying vehicle failures and predicting future workshop demand. This can be useful for preprocessing data before applying a more complex predictive model. Once the data is segmented, the demand patterns in each segment can be studied in more detail to estimate future demand.

Each cluster must be analyzed by vehicle model, just as was done for component wear, to have a more precise definition of expected demand in the service workshop. Parallel Computing with CUDA This type of computing allows for processing large amounts of data more efficiently, resulting in significant improvements in response times and the ability to handle complex tasks. CUDA stands for Compute Unified Device Architecture and is a parallel computing platform developed by NVIDIA. It allows for the rapid and efficient execution of Artificial Intelligence algorithms for real-time data processing and for training neural networks such as SOMs, which require large volumes of data for training, as can be seen in Tosida et al. (2017).

These types of self-organizing networks or maps (SOMs) are a type of unsupervised neural network that allows data classification and the discovery of patterns in large information sets (Guglielminotti de Inés, 2022). As can be seen in Miljković (2017), SOMs have been successfully applied in the classification of complex data, such as the diagnosis of faults in electric motors as can be seen in (Bossio et al., 2017). In the automotive field, these networks can analyze vehicle maintenance history and predict service needs, which contributes to better resource planning and the optimization of operational processes in workshops.

The use of self-organizing neural networks (SOMs) and CUDA parallel computing has proven to be an effective solution for predicting service demand in automotive workshops and improving operational efficiency. This approach, based on the collection and analysis of historical vehicle data, offers great potential for optimizing workshop management, reducing wait times, and improving customer satisfaction.

Finally, the application of SOM artificial neural networks in a structured information ecosystem that allows for the maximization of its processing can generate a useful tool for automotive dealerships, enabling them to provide better customer service for complex fault repairs, increasing customer satisfaction and thus increasing vehicle retention at the service center for vehicles with mileages above 70,000 km, which will allow for an increase in the dealership's financial income.

Therefore, in a subsequent work, a classification neural network will be used, using the input variables for training the network, the clusters generated in this article.

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