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Research Article

Neural networks for forecasting irregular demand in an Automotive Diagnostic Centre

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Abstract

This study investigates the prediction of demand in an Automotive Diagnostic Centre (ADC) in Bucaramanga, Colombia, applying advanced neural network techniques to three services: technical inspections for motorcycles, private cars, and public service vehicles. Utilising daily data from December 2019 to December 2021 (628 observations), the squared coefficient of variation of demand (CV^2) and the average demand interval (ADI) are employed to classify demand, following the methodology of Syntetos & Boylan (2005b). Five Deep Learning models were evaluated: RNN, Bidirectional LSTM, CNN, GRU, and MLP, adopting a recursive approach for prediction. The findings reveal that despite the promises of forecasting algorithms and their success in other sectors, their performance in the context of ADCs is limited. Evaluation metrics, including RMSE, MSE, MAE, r2_score, and MAPE, reveal that although the LSTM model exhibits the best overall performance, no model achieves precise and reliable prediction due to the complexity and irregularity of demand. This finding underscores the need for continued research in demand forecasting and suggests exploring hybrid approaches or more specialised models. The variability in performance across models and services reflects the importance of tailoring predictive approaches to the specific characteristics of each demand segment. The principal contribution of this study is the innovative approach in applying neural networks to irregular demand in ADCs, an area hitherto little explored. It highlights the need to integrate external variables and develop adaptive management practices. Future research should focus on the integration of external factors and the development of hybrid models and mitigation strategies for efficient management of demand uncertainty.

Keywords: Demand forecasting; Neural networks; Automotive Diagnostic Centre; Demand variability; Model optimization.

1. Introduction

In the era of digitalization and automation, Automotive Diagnostic Centres (CDAs) face unique challenges in the efficient management of their operations, one of the most critical being the accurate prediction of service demand. The inherently irregular nature of this demand, influenced by factors such as market trends, vehicle maintenance policies, and technological advancements, significantly complicates resource planning and inventory management (Steuer et al., 2018). Accurate demand estimation is vital to optimize resource allocation, minimize wait times, and maximize customer satisfaction (Zenchenko & Grigoriev, 2020). Intermittent demand forecasts are challenging, considering their irregular and random nature. This type of demand is distinguished by having zero demand periods mixed with variable and non-zero demand periods (Amirkolaii et al., 2017). This contrasts with the forecast of non-intermittent demand, in which the only uncertainty lies in the magnitude of demand(Hoffmann et al., 2022). In the case of intermittent demand, the uncertainty lies both in the timing of the positive demand and in its magnitude. Thus, those who are dedicated to forecasting this type of demand are faced with the challenge of determining not only the amount of demand, but also the time at which it will manifest itself (Zhang et al., 2023).

The irregularity of the demand in the CDAs has a direct impact on the operability and efficiency of these centres. Fluctuations in demand can lead to under- or over-utilization of resources, affecting the profitability and quality of the service offered. Traditional forecasting methods, based on statistical models or qualitative approaches, often fail to capture the inherent volatility and complexity of demand in the automotive sector, resulting in inaccurate predictions and suboptimal decisions, which can have a negative impact on inventory planning and staffing (Bremen, s. f.). Despite the increasing globalization of supply chains and the increasing diversity of products and services, traditional forecasting methods have proven insufficient to address the complexities of intermittent demand, highlighting the need for more sophisticated and adaptive approaches(Zhang et al., 2023). In this context, neural networks emerge as a promising tool, offering the ability to learn and adapt to complex, non-linear patterns in historical demand data (Eseye et al., 2019). This study aims to explore the use of neural networks to improve the forecasting of irregular demand in CDAs. Neural networks, with their ability to learn and adapt to complex, non-linear patterns in data, offer a potentially more effective solution to address the peculiarities of demand in this sector. By applying these advanced machine learning techniques, we seek to provide

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a more accurate and adaptable approach to forecasting demand in CDAs, overcoming the limitations of conventional methods.

The main contribution of this study lies in its innovative approach, the application of neural networks in the specific context of irregular demand in CDAs, an area that until now has been little explored, likewise, this research demonstrates that, despite the promising applications of different algorithms for demand forecasting, as demonstrated in studies such as those by Hoffmann et al. (2022a), Zohdi et al. (2022), Zhang et al (2023), and others, seeks to present a discussion that refutes or questions previous results in the specific context of CDAs. Previous research has shown how certain neural network configurations outperform traditional statistical methods in predicting irregular demand, especially in sectors such as spare parts (Lolli et al., 2017; Muhaimin et al., 2021; Svetunkov & Boylan, 2023) & Maintenance (Zohdi et al., 2022). However, our study reveals that, in the case of CDAs, although neural network models have considerable potential, their effectiveness is limited in highly variable and unpredictable demand scenarios. This finding highlights the need for continued research and the development of hybrid approaches or more specialized models to manage variability and intermittency in demand.

Finally, this article is structured in the following sections: methodology, where the algorithms and techniques used are detailed; results and discussion, where the performance of the models in the context of the CDAs is analyzed; and finally, the conclusions, where key findings are summarized and future directions for research in this field are proposed.

2. Review Literature

Intermittent data forecasting has been a key area of research since the 1970s. Intermittent demand time series are distinguished from traditional series by the frequent presence of periods of no demand, a concept initially introduced by Croston (1972), in his research, highlighted the inadequacy of conventional time-series methods, such as exponential smoothing, for this type of demand and proposed an alternative forecasting method specially designed for intermittent demand time series (Croston, 1972). Later research, such as the work of Willemain et al. (2004), confirmed the adequacy of Croston's method for these series, showing improvements over traditional methods. However, Syntetos and Boylan (2001) They identified a bias in Croston's original method and proposed a modified version to correct it, achieving greater accuracy in their predictions. Hyndman and Shenstone's analysis (2005) They suggest that although Croston's method is useful in practice and outperforms conventional methods, it has certain limitations. They argue that their basis in exponential smoothing implies an assumption of continuous data, including negative values, which does not align with the reality of intermittent demand that is inherently integer and not negative. In addition, although Croston claimed that their method assumes independence between demand size and demand intervals, Willemain et al. (2004) They questioned this assumption. Nikolopoulos et al. in 2011 explored data aggregation to reduce zeros in time series, but found that this approach can miss useful information (Nikolopoulos et al., 2011).

The literature has also treated intermittent and global demand in a similar way, using methods such as bootstrapping and neural networks. Mukhopadhyay et al.,(2012) They suggested that non-traditional methods could outperform traditional ones in certain contexts. Nikolopoulos (2021) He noted that the focus on demand for spare parts is too narrow, as intermittent demand occurs in various sectors. As a different perspective, Sarlo et al.(2023) They developed score-based models that address the absence of complete predictive distributions and the handling of excess zeros, proving to be competitive and a viable option for professionals in the retail sector.

Given the specific nature of intermittent demand, neural networks have evolved as a crucial tool in demand forecasting, notable for their ability to model nonlinear complexities and adapt to irregular patterns. Several studies have addressed the comparison between artificial neural networks (ANNs) and conventional forecasting methods, as well as the incorporation of improvements in ANNs to optimize their performance. Gutierrez et al. (2008) They proposed an RNA methodology for time series of variable demand, surpassing Croston's method and Syntetos' and Boylan's modification in their experiments (Syntetos & Boylan, 2005a). Nasiri Pour et al. (2008) They compared several ANNs to the SBA in 30 time series, finding that their new hybrid network was more effective. Mukhopadhyay et al. (2012) modified the architecture proposed by Gutiérrez et al. (2008), achieving promising results. Kourentzes (2013) developed two ANN models, called NN-Dual and NN-Rate, which allow for the interaction between demand and demand intervals.

Studies such as those by Hoffmann et al. (2022a) and Lolli et al. (2017) They have demonstrated the effectiveness of neural networks, especially in irregular and intermittent demands. Architectures range from multilayer networks to Transformer models, as evidenced in Zhang et al. (2023), each adapting to different needs and demand contexts. These advances reflect a continued evolution in the application of neural networks, moving beyond single-layer configurations to more complex and specialized structures. In the work of Tian et al. (Tian et al., 2021), Neural networks have outperformed traditional methods, highlighting the relevance of integrating expertise and inventory data into prediction models. Kourentzes (2013) reveal the effectiveness of neural networks, especially RNNs, in predicting intermittent demand patterns in the retail and aftermarket sector. The literature review demonstrates the effectiveness and versatility of neural networks in predicting demand in a variety of sectors.

However, it underlines the need for more focused studies in specific sectors such as CDAs. Existing studies have focused primarily on industries with similar demand characteristics, but do not directly address the unique challenges of CDAs. This gap in the literature highlights the originality and relevance of current research, which seeks to apply and adapt neural network techniques in a little-explored context, thus contributing to a better understanding and management of irregular demand in this specific sector. The integration of specialized knowledge and the adaptation of models to the particularities of each industry emerge as key elements for progress in this field.

3. Material and Methods

3.1. Data

The data used in this research come from a CDA Automotive Diagnostic Centre located in the city of Bucaramanga, Santander, Colombia. The company provided daily demand data for three main services of the CDA: techno mechanical revisions of motorcycles, private cars, public service cars. The time series of data spanned from December 1, 2019 to December 12, 2021, totalling 628 observations. The behaviour of each of the services is presented below.

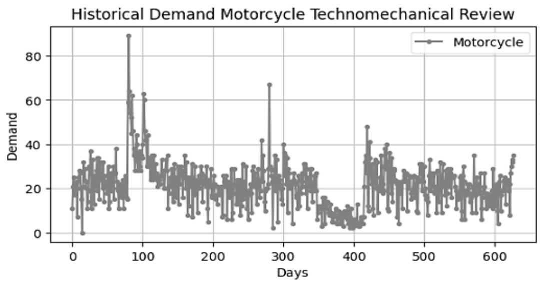

Fig .1. Behaviour demand for techno mechanical review service for motorcycles

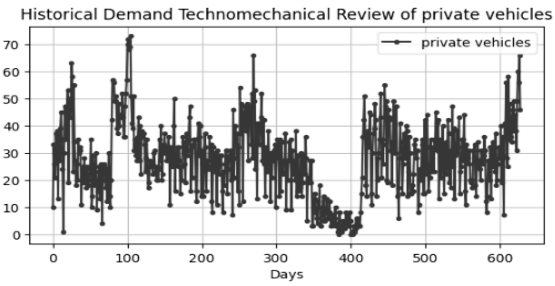

Fig .2. Behaviour demand for techno mechanical review service for private vehicles

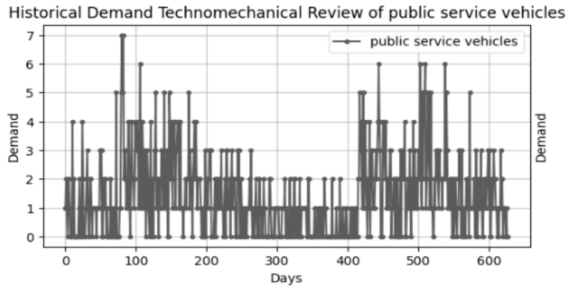

Fig .3. Behaviour demand for techno mechanical review service for public service vehicles

Table 1.
Descriptive Statistics of the Demand for Services in the Automotive Diagnostic Centre

	Motorcycle	Particular	Public
Quantity	628	628	628
Stocking	21.3	27.5	1.4
Desv. Standard	10.1	13.6	1.3
Minimum Value	0.0	0.0	0.0
25%	15.0	19.0	0.0
50%	21.0	28.0	1.0
75%	27.0	36.0	2.0
Maximum Value	89.0	73.0	7.0

Following the relevant literature, two key metrics were adopted to characterize and classify demand: the coefficient of variation of demand squared (CV^2) and the average demand interval (ADI). These metrics make it possible to identify noise and intermittency levels in the data, thus facilitating a better understanding and prediction of demand patterns. The CV^2 is an indicator of the relative dispersion of demand and is calculated as the variance over the square of the mean demand. Higher CV^2 values indicate greater relative variability, which may mean that demand is more difficult to predict. On the other hand, the ADI measures the frequency with which claims are recorded, calculated as the total number of periods divided by the number of periods with demand. A higher ADI suggests more intermittent demand, with more frequent periods of zero demand (Amirkolaii et al., 2017).

Using the classification scheme proposed by Syntetos & Boylan.,(2005b) Experimental cut-off values of CV^2=0.49 and ADI=1.32 were established to classify demand into four categories: mild, erratic, intermittent and uneven. These cut-off values are representative of the variability in quantity and demand intervals, respectively (Table 2).

Table 2.
Four Types of Demand Considered and Representation of Variability

Type of Claim	Intervals Between Demand	Quantity
Smooth	Low	Low
Erratic	Low	High
Intermittent	High	Low
Unequal	High	High

In our analysis, the following results were obtained for each type of service:

Motorcycles: CV^2 of 0.229 and ADI of 1.002, classifying demand as mild, indicating consistent and predictable demand.

Private Vehicles: CV^2 of 0.244 and ADI of 1.005, also indicating a soft demand.

Public Service Vehicles: CV^2 of 0.966 and ADI of 1.444, classifying demand as uneven, reflecting a demand with high levels of variability and intermittency.

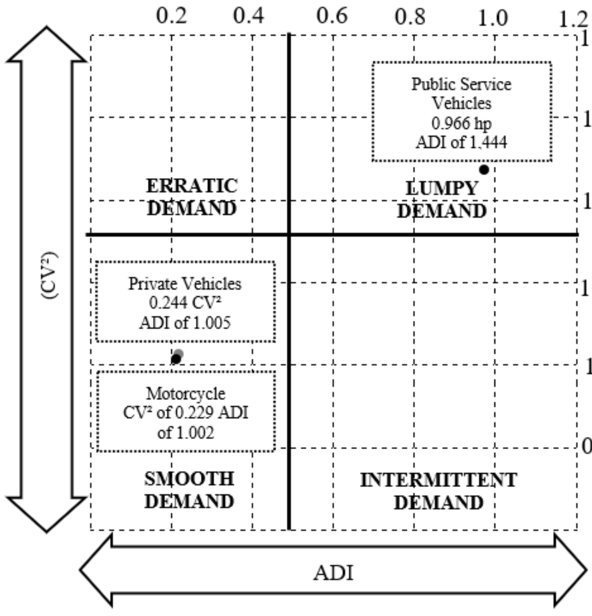

Fig .4. Behaviour demand for techno mechanical review service of public service vehicles

A detailed understanding of demand variability and intermittency, expressed through CV^2 and ADI metrics, not only informs the initial selection of forecasting models, but also provides an essential interpretive framework for the results obtained.

3.2. Deep learning models

The aim of the study is to test the applicability and performance of neural networks in a real context with data extracted from an automotive service centre. The following Deep Learning models were selected considering that they have been frequently used for time series prediction and have reported satisfactory results (da Silva & Meneses, 2023; Jiang et al., 2021).

Recurrent Neural Networks (RNNs): It focuses on modelling the sequentially of data, being especially valuable for time series where the relationship between consecutive events is significant. This model helps to understand the evolution of demand over time (Fierro, 2020). Our simple recurrent neural network (RNN) model consists of three RNN layers with 100 units each, using the hyperbolic tangent activation function and a uniform kernel initializer. The first two RNN layers return complete sequences, while the third delivers a single output. The output layer is a dense layer with linear activation.

Bidirectional LSTM Neural Networks: This model is characterized by its ability to learn dependencies in both temporal directions of the data, which is crucial for capturing the full dynamics of the time series in irregular demand forecasting(da Silva & Meneses, 2023). This architecture leverages information from both the past and the future to improve the accuracy of predictions.(Guerrero, 2020). In our study, we implemented a Bidirectional LSTM model to capture dependence on both future and past directions of the time series. The architecture consists of a bidirectional LSTM input layer with 50 units, designed to process sequences in both forward and reverse order. The output layer employs a *TimeDistributed* layer with linear activation, suitable for time series prediction.

Convolutional Neural Networks (CNN): This model It is known for its efficiency in processing sequential data, especially useful in identifying temporal and spatial patterns in automotive diagnostic demand. Its structure is ideal for extracting and learning relevant features of the time series. This type of neural network was originally designed to process image data, but the same properties that make convolutional neural networks conducive to computer vision problems make them highly relevant for signal processing. Time can be treated as a spatial dimension, like the height or width of a 2D image. These are the 1D convolutional networks. 1D convolution layers obtain new convoluted sequences through filters that interpret certain characteristics of the original sequences that allow local patterns to be recognized in the same (Fierro, 2020). In this study, the convolutional neural network (CNN) model was constructed with an input layer followed by two sets of convolutional and maxpooling layers. Each convolutional layer contains 220 filters with a core size of 2 and a hyperbolic tangent activation function. Dropout layers are included to improve the generalizability of the model. The output layer is a dense layer with a single unit.

Gated recurrent unit (GRU) neural networks): This model, with its simplified structure compared to LSTM, provides an efficient alternative for modelling temporal dependencies. It is particularly effective in handling shorter time series, avoiding the fading gradient problem by being computationally lighter (Cea Morán, 2020). The implemented recurrent gate unit (GRU) model follows a similar structure to the RNN model, with three GRU layers of 100 units each. As in the RNN model, the first two GRU layers return complete sequences and the third provides a single output. The output layer is a dense layer with linear activation.

Multilayer Perceptron Model (MLP): This model is a direct-fed neural network that is used to capture linear and nonlinear relationships in data. Its multi-layered structure allows a detailed and in-depth approach to the demand forecasting process, being useful for understanding complex relationships in the data (Amirkolaii et al., 2017). The implemented model was composed of a flattening layer and seven dense layers, each with 70 units and hyperbolic tangent activation. The output layer is a dense layer with a single unit. This model is compiled with an Adam optimizer and a mean square error (MSE) loss function.

3.3. Hyper parameter Optimization

The hyper parameters were fine-tuned with the *RandomizedSerachCV* algorithm from the Sklearn Python library. Since the models used require a lot of computational power, due to the large number of parameters to test. Using the *RandomizedSerachCV* function, it is possible to perform a random search that tries to identify the best structure for the model; Not all possible combinations of values, but only a certain number of them. In this way, even if the total number of possible combinations is high, it is possible to limit the training time.

3.4. Prediction horizon

There are three alternative ways to produce multi-period predictions with machine learning models (31). The recursive strategy involves adding the last prediction of the last timestep as input to the next prediction; In this way, a single-output model and a recursive prediction system up to the defined limit are established. The direct strategy, where a model is trained for each time step to be predicted (32). A combination of the previous two, where several models and a recursive system are used between the models themselves. In the present research, the recursive prediction approach was used, considering that one of its main advantages is its simplicity and reduced computational load. The disadvantage is that, as the predictive horizon increases, the accuracy of new predictions tends to deteriorate.

3.5. Evaluation metrics

RMSE. The mean square error or mean square deviation is one of the most commonly used measures to assess the quality of predictions. Formally it is defined as follows:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y'_i - y_i)^2}{n}} \tag{1}$$

MSE. The mean square error evaluates the average squared difference between the observed and predicted values. It is defined as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2 \tag{2}$$

MAE. The mean absolute error corresponds to the average of the absolute differences between the actual values and the predictions. It is calculated using the following equation:

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|y_i - y_i^{'}\right| \tag{3}$$

MAPE. The Mean Absolute Percentage Error measures the size of the (absolute) error in percentage terms. It is calculated using the following equation:

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{y_i - y_i^{'}}{y_i}\right| \tag{4}$$

Coefficient of determination (R2). It is the proportion of the total variance of the variable explained by the regression. It serves to reflect the goodness of fit of a model to the variable it is intended to explain. It is defined as follows:

$$R^2 = \frac{\sum_{t=1}^{T}\left(\hat{Y}_t - \bar{Y}\right)^2}{\sum_{t=1}^{T}(Y_t - \bar{Y})^2} \tag{5}$$

4. Results and discussion

The following section details the results obtained from the models evaluated across multiple metrics which provide a comprehensive assessment of the models' performance, but also shed light on their ability to capture and predict fluctuations in demand for the various CDA services. Through this study, we seek to contribute significantly to the field of artificial intelligence applied in operations and service management, providing valuable insights for academics and practitioners alike. The results obtained are then broken down and analysed.

4.1. Demand Forecast Results Techno Mechanical Revision Motorcycles

Table 3.
Results of the evaluation metrics of the Forecasts Demand Techno Mechanical Review Motorcycles

Model	RMSE	MSE	DUDE	ASM	r2_score
LSTM Motorcycles	6.453	41.648	5.135	0.362	0.018
CNN Motorcycles	7.033	49.473	5.435	0.420	-0.165
RNN Motorcycles	6.467	41.822	5.128	0.363	0.014
GRU Motorcycles	6.488	42.098	5.126	0.372	0.008
MLP Motorcycles	6.561	43.053	5.206	0.379	-0.014

Based on the demand behaviour of the techno mechanical revision of motorcycles classified as smooth, with a Coefficient of Variation (CV^2) of 0.229 and an Aggregate Demand Index (ADI) of 1.002. These metrics indicate consistency and predictability in demand, which is a favourable factor for forecasting models. However, the results obtained from the different neural network models indicate an underlying complexity in the data that affects the effectiveness of the forecast. The Bidirectional LSTM model, with an RMSE of 6.453, reflects an average prediction error of about 30% of the mean demand, which is a reasonable but not optimal accuracy, given that the mean is 21.32 and the standard deviation is 10.20. This level of error suggests that although the model captures the overall trend, there is a significant margin of inaccuracy. In addition, its r2_score of 0.018, while low, indicates some ability to capture variability in the data, although it suggests that demand dynamics are not being fully explained. This phenomenon may be attributable to the nature of the time series which, despite its apparent smoothness, could present complex patterns not fully captured by the model.

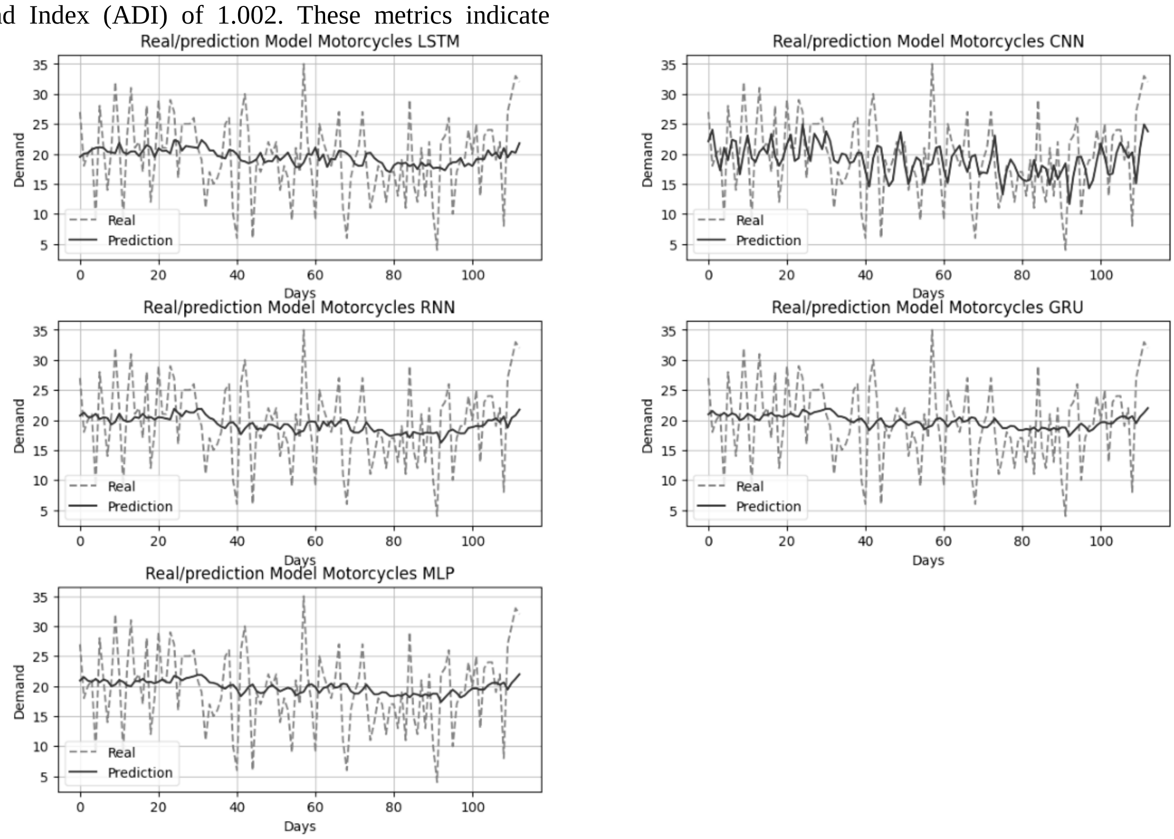

Fig .5. Results evaluation metrics Forecasts Demand Techno Mechanical Review Motorcycles

In the case of the CNN model, with an RMSE of 7.033 and a r2_score of -0.166, they indicate that this model is not only less accurate, but also has difficulty adjusting to the variability of the data. This could be due to the nature of CNNs, which are better suited for capturing spatial features and may not be as effective for time series where temporal relationships are more critical. The RNN and GRU models exhibit similar performance to LSTM in terms of RMSE, but their low r2_scores suggest a limited ability to capture variability in the data. The MAE for these models, around 5, indicates that the predictions deviate on average 5 units from the actual values, which is a moderate error compared to the average demand. The conceptually simpler MLP model features the highest RMSE of 6.562 and a negative r2_score of -0.014, indicating poor ability to predict demand compared to the other models. This may be because the linear and nonlinear relationships in the data are more complex than the MLP can efficiently handle.

Despite the hyper parameter adjustment made, these results demonstrate the need for a more in-depth analysis of the nature of demand data. The choice of the model and the configuration of its parameters should consider not only the accuracy in terms of forecast error but also the ability of the model to generalize and capture the underlying dynamics of the data. These findings also highlight the importance of understanding the limitations and strengths of different neural network approaches in the specific context of demand forecasting in Automotive Diagnostic Centres.

4.2. Demand forecast results techno mechanical revision of private vehicles

Table 4.
Results of the evaluation metrics of the Forecasts Demand Techno Mechanical Review Private Vehicles

Model	RMSE	MSE	MAE	MAPE	r2_score
LSTM Private Vehicles	9.984	99.686	7.798	0.333	0.203
CNN Private Vehicles	9.599	92.158	7.705	0.349	0.263
RNN Private Vehicles	9.820	96.439	7.803	0.354	0.229
GRU Private Vehicles	10.001	100.037	7.835	0.333	0.200
MLP Private Vehicles	9.844	96.916	7.767	0.343	0.225

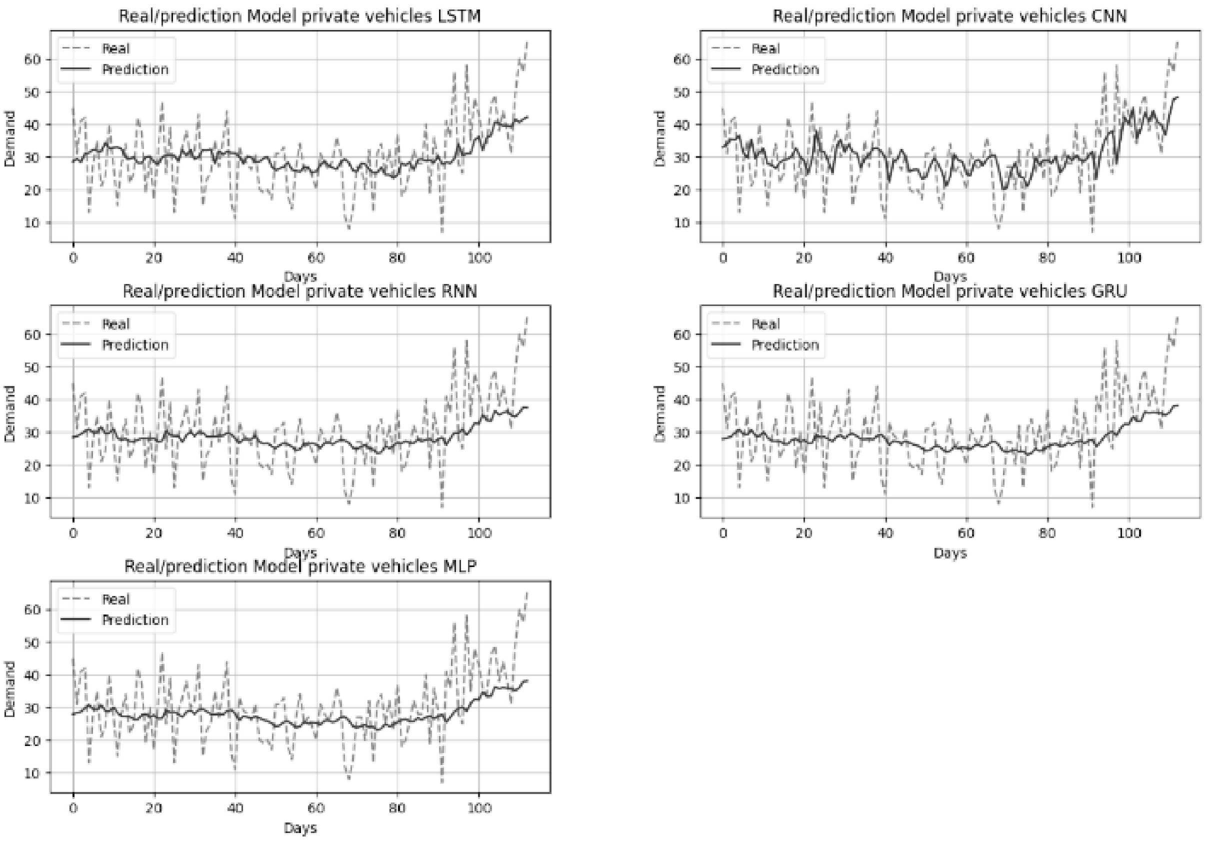

Fig .6. Results evaluation metrics Forecasts Demand Techno Mechanical Review Private Vehicles

In relation to the forecast of demand for techno mechanical revision for private vehicles, in which there is again a demand classified as mild, with a Coefficient of Variation (CV^2) of 0.244 and an Aggregate Demand Index (ADI) of 1.005, indicators similar to those of motorcycles, which show a consistent and predictable demand, being a generally favourable scenario for predictive models. However, the results of neural network models show significant variations in their performance, indicating the existence of inherent challenges in accurately predicting this specific demand. The LSTM model for private vehicles has an RMSE of 9.984, which, compared to a mean demand of 27.5 and a standard deviation of 13.6, indicates a substantial error in the predictions. This level of RMSE, which is above 35% of the average, points to considerable inaccuracies in the model. However, its r2_score of 0.203 suggests a moderate ability of the model to explain the variability of the data, although not optimally. This performance may be influenced by the increased complexity in particular vehicle demand trends, which might not be fully captured by the LSTM architecture. The CNN model shows an RMSE of 9.600 and a r2_score of 0.263, indicating better performance compared to the LSTM model. This result can be attributed to the effectiveness of CNNs in extracting relevant features from data, especially in time series with more complex patterns. Although the RMSE remains high, the improvement in r2_score suggests better capture of data variability.

The RNN and GRU models show similar performance, with RMSEs of 9.820 and 10.002, respectively, and r2_scores of 0.229 and 0.200. These results are consistent with the nature of these models, which are effective at capturing short-term dependencies in time series. However, the magnitude of the RMSE indicates that both models face challenges in accurately predicting demand for particular vehicles. the MLP model shows an RMSE of 9.845, which is slightly lower than some of the other models, and a r2_score of 0.225. Although MLP models are generally considered less sophisticated for time series, this result could indicate that demand for particular vehicles fits well with the linear and nonlinear relationships that MLPs can efficiently model.

In terms of error metrics such as MAE and ASM, all models exhibit similar values, suggesting that although there are differences in their RMSE and r2_scores, the magnitude of absolute errors is comparable between models. This indicates a consistency in the overall accuracy of the predictions, although none stand out for exceptionally high performance.

In general, the models show an ability to predict demand, none of which stands out for exceptionally high performance. This may be due to the inherent complexity in particular vehicle demand patterns, which might require more advanced approaches or a combination of models to improve forecast accuracy. These results underline the importance of continuous evaluation and optimization of models in the field of demand prediction in Automotive Diagnostic Centres.

4.3. Demand Forecast Results Techno Mechanical Revision of Public Service Vehicles

Conventionally, in mathematical equations variables and anything that represents a value appear in italics, while chemical equations are displayed in roman, except for positional prefixes. The styles of this template reflect that general difference, but you can change that as required. You may choose to number equations for easy referencing. In that case the number should appear at the right margin.

Table 5
Results of the evaluation metrics of the Forecasts Demand Techno Mechanical Review Public Service Vehicles

Model	RMSE	MSE	MAE	MAPE	r2_score
LSTM Public	1.205	1.453	0.924	11885235000.0	0.035
CNN Public	1.263	1.596	0.947	111104026000.0	-0.059
RNN Public	1.217	1.483	0.923	11294165000.0	0.015
GRU Public	1.202	1.446	0.924	11538203000.0	0.039
Public MLP	1.231	1.515	0.912	104596614000.0	-0.006

In the analysis of the demand for techno mechanical revision for public service vehicles, we are faced with a scenario of high variability and intermittency, characterized by a Coefficient of Variation (CV^2) of 0.966 and an Aggregate Demand Index (ADI) of 1.444. These metrics classify demand as uneven, presenting a significant challenge to forecasting models due to their unpredictability.

For this case, the LSTM model has an RMSE of 1.206. Given that the mean demand is 1.404 and the standard deviation is 1.381, an RMSE of this magnitude suggests that the errors in the model's predictions are comparable to the natural variability of the data. This indicates reasonable, but not exceptional, accuracy in a context where demand is inherently unpredictable.

The CNN model, with an RMSE of 1.264 and a negative r2_score of -0.060, shows a slightly higher error in predictions compared to the LSTM. The negative r2_score here implies that the CNN model is not only inaccurate, but also ineffective at capturing the variability of the data, which may be due to the complex nature of the time series in question. This decrease in performance can be attributed to the fact that CNNs, despite their effectiveness in pattern recognition, may not be as well suited to capturing the complex temporal dependencies present in utility vehicle demand data.

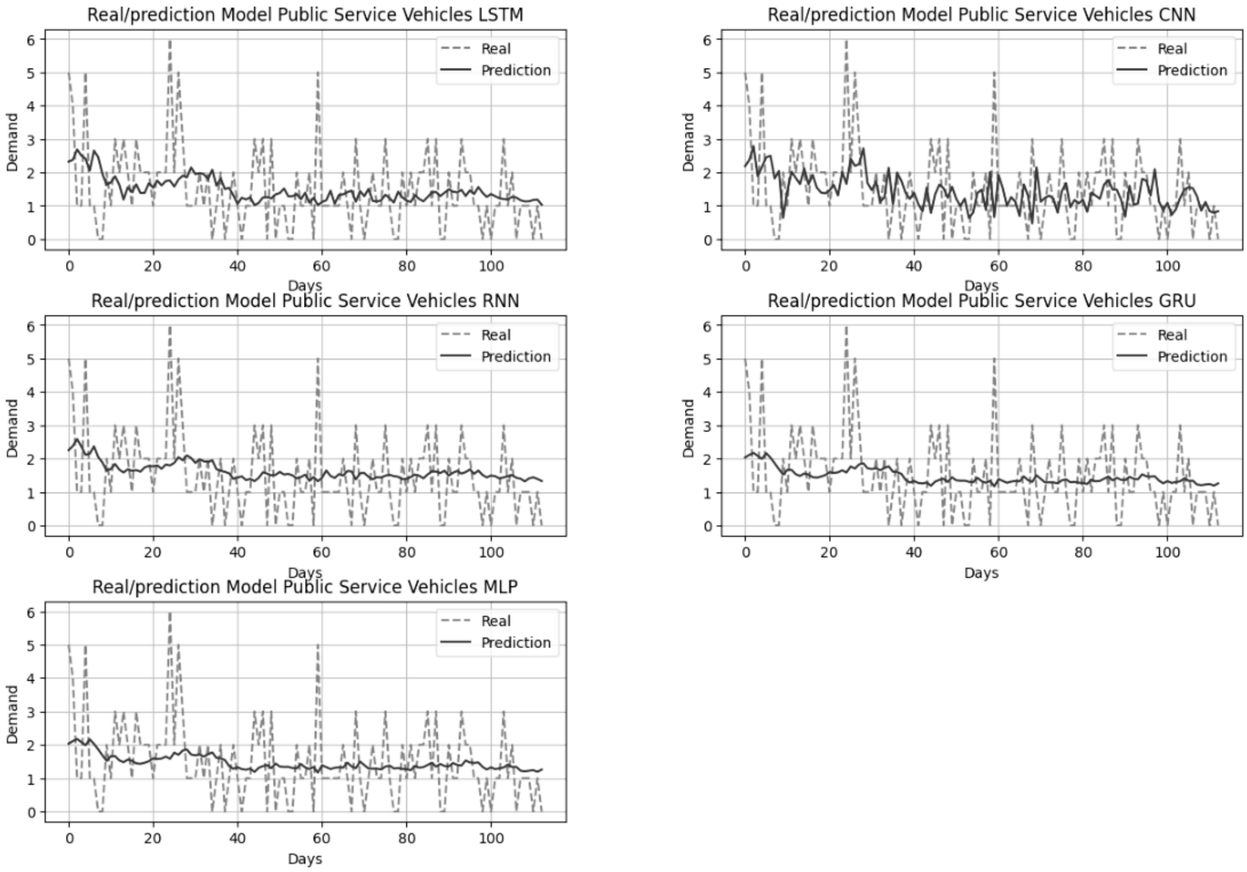

Fig .7. Results evaluation metrics Forecasts Demand Techno Mechanical Review Public Service Vehicles

The RNN and GRU models, with RMSEs of 1.218 and 1.203 respectively, show similar performance to LSTM. These RMSE values, slightly higher than that of the LSTM model, indicate comparable accuracy, but with a slight decrease. The mildly positive r2_scores of these models suggest a moderate ability to explain the variability of the data, although there is still room for improvement. The MLP model, with an RMSE of 1.231 and a r2_score of -0.006, reflects unsatisfactory performance compared to the other models. This result underscores the difficulty of applying direct-fed neural networks, such as MLPs, to problems where temporal dependencies and unpredictable variations are prominent.

Unlike the previous cases, in the demand forecast for techno mechanical overhauls of public service vehicles, none of the models achieved outstanding performance, reflecting the challenges inherent in demand prediction in scenarios of high variability and intermittency. This suggests the need to explore more advanced or hybrid approaches to improve accuracy in such contexts.

4.4. General analysis of results

In general, this study evidenced significant variations in the performance of the neural network models in the prediction of demand for the three services evaluated in an Automotive Diagnostic Centre (ADC). First, the classification of demand in this study was based on two key indicators: The Coefficient of Variation (CV^2) and the Aggregate Demand Index (ADI). These metrics are crucial to understanding the nature of demand for each of the services analysed. Generally speaking, a high CV^2 coupled with a high ADI characterizes "uneven" demand, which translates into high variability and intermittency in demand. For motorcycle techno-mechanical reviews, ranked with mild demand, no neural network model showed exceptional performance. The Bidirectional LSTM model, while exhibiting reasonable accuracy with an RMSE of 6.453 and a r2_score of 0.018, did not fully capture demand dynamics. The CNN, RNN, and GRU models exhibited similar returns to the LSTM in terms of RMSE, but with limitations in addressing data variability. The MLP model, despite its simplicity, registered the highest inaccuracy.

In the case of private vehicles, which also presented a soft demand, a similar trend was observed. The LSTM model performed moderately with an RMSE of 9.984, while the CNN model showed better performance, possibly due to its ability to extract complex features from time series. The RNN, GRU, and MLP models performed slightly better than the LSTM, though not significantly noting, reflecting the complexity inherent in the demand for these vehicles. Finally, in the analysis of public service vehicles, characterized by highly variable and intermittent demand, the challenge was even greater. The LSTM model showed reasonable accuracy with an RMSE of 1.206, but all models, including CNN, RNN, GRU, and MLP, faced significant difficulties in adequately capturing data variability, as indicated by their r2_scores. The MLP model, although with a similar RMSE to the other models, demonstrated notable limitations in this context of high variability.

The main reason behind the suboptimal results obtained in this study is due to the inherently unpredictable and highly variable nature of demand in the context of a CDA. Neural network models, while advanced and capable of capturing complex patterns, have limitations when faced with data with high variability and little consistency. In the case of motorcycles and private cars, where demand is classified as soft, models still face difficulties due to the subtlety of variations in demand that are not always captured by the models. For utility vehicles, with demand classified as uneven, the challenge is intensified due to high irregularity and low predictability, resulting in RMSEs and r2_scores reflecting a limited ability of the models to make accurate forecasts.

On the other hand, the complexity of the time series and the possible presence of nonlinear patterns and complex temporal relationships in demand data add another layer of difficulty. Models such as LSTM, CNN, RNN, GRU, and MLP, while versatile and powerful, may not be fully equipped to handle such levels of irregularity without specific tweaks and optimizations. Additionally, the applicability of the models may be limited by the need for a large amount of historical data and the computational complexity involved in training deep learning models. Another challenge encountered was the selection and optimization of suitable hyper parameters for each model, which is crucial for its performance, which turns out to be an intensive and technical process.

This study reveals that, although neural network models have considerable potential, their effectiveness is limited in highly variable and unpredictable demand scenarios, as is the case in Automotive Diagnostic Centres. This finding underscores the need for continued research and development in the field of demand forecasting, especially in contexts where irregularity is a dominant feature. In addition, it suggests the possibility of exploring hybrid approaches or more specialized models that can better handle variability and intermittency in demand.

5.1 Reas of future research

Future research could explore the integration of external data, such as economic or climatic variables, to improve the accuracy of models in CDAs. In addition, it would be beneficial to investigate hybrid approaches that combine different types of deep learning models or that integrate machine learning techniques with traditional statistical methods. Another area of interest could be the development of models that dynamically adapt to changes in demand patterns, thereby improving their ability to handle variability and intermittency in different automotive diagnostic service contexts.

5. Conclusion

This study on demand prediction in Automotive Diagnostic Centres (CDAs) using neural network models reveals critical points in both theory and practical application. In situations where models fail to achieve optimal results, a plausible explanation lies in the intrinsic nature of demand data. High variability, evidenced by a high CV^2, and significant intermittency, marked by a high ADI, can seriously limit the predictive capacity of any model, including neural networks. This understanding is crucial not only for model selection but also for providing a perspective through which forecasts can be interpreted and improved. It is essential to recognize the nature of demand in each service category, which allows for adjusting performance expectations and developing more resilient and adaptive management practices in CDAs.

In addition, the variability in model performance by service type highlights the importance of considering the unique characteristics of each demand segment when applying forecasting models. External factors such as economic conditions, government regulations, and market trends play a crucial role and can significantly influence demand. Therefore, these factors must be considered to improve the accuracy of predictive models. The choice of the most appropriate model for each service in a CDA should be based on a detailed assessment of the specific needs and demand characteristics of each service.

It is highlighted that, although Deep Learning models are powerful tools, their effectiveness is closely linked to the detailed understanding of demand patterns. The ability to accurately predict demand can facilitate better resource allocation, improve customer satisfaction, and optimize operational efficiency in CDAs. Future research should focus on the integration of external variables, the development of hybrid and adaptive models, and the implementation of mitigation strategies to improve the management of uncertainty in demand.

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