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Fuzzy Inference System for Predicting Functional Service Life of Concrete Pavements in Airports

A. J. Prieto [1,*], F. Guiñez [1], M. Ortiz [2] and M. González [1]

[1] Department of Construction Engineering and Management and Concrete Innovation Hub UC (CIHUC), School of Engineering, Pontificia Universidad Católica de Chile, Avenida Vicuña Mackenna, 4860, Santiago 7820436, Chile
[2] Directorate of Airports, Ministry of Public Works, Government of Chile, Santiago 9020000, Chile
* Correspondence: andres.prieto@uc.cl; Tel.: +56-988319810

Abstract: Concerning one of the most important tasks of road structure management is the development of methods to predict their own functional or physical service life, which allows for objectively evaluating the state of road structures that are being considered or are already in operation with minimal labor and monetary incomes. Fuzzy logic systems constitute one successful methodology used for the valuation of pavement degradation. The clustering that focuses on pavement degradation conditions is normally performed by a visual inspection or using data collected by automated distress measurement equipment. Fuzzy sets theory provides different advantages for including a certain degree of uncertainty in the pavement performance index, subjective analysis, and maintenance assessments and can greatly improve consistency and reduce subjectivity in the degradation process. The main objective of this study was to develop a new fuzzy logic-based model to predict the functional service life of concrete pavement conditions and maintenance action evaluations concerning the airport network of Viña del Mar, Central Chile, and using pavement distress data from the Directorate of Airports, Ministry of Public Works of Chile. The proposed fuzzy logic model can be remarkably beneficial for design, construction, and maintenance, to evaluate design decisions for the measurable and objective valuation of deviations in the quality of construction, and for timely forecasting work based on continuous observing of the current infrastructure system.

Keywords: concrete pavements; fuzzy logic; airports; decision-making; service life

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1. Introduction

Currently, a horizontal infrastructure, in terms of pavements, is one of the most significant assets of nations, and it is also normally associated with an increased productivity of industries, a greater use of trade, and a high quality of life [1]. This infrastructure is usually managed by systematic methodologies, whose purpose is to define maintenance, rehabilitation, and improvement strategies to maintain a minimum level of network service by efficiently directing the available resources [2,3]. Since its emergence in the early 1970s, pavement management systems (PMS) have been evolving through the incorporation of different methodological tools [4]; however, it has been widely evidenced in different areas of the industry that the inertia to change is not usually enough, which, among other causes, is a product of the fragmentation of the sector. Thus, this situation generates delays in the incorporation and generalization of the use of new digital tools that are involved in the new methodologies link to the technological revolution of the sector [5]. In this sense, despite recent advances in materiality, construction methods, life cycle analyses, service life prediction (physical and functional) and pavement maintenance and rehabilitation (M&R) techniques, many of the current massively used PMS perform based on traditional techniques, which demonstrates a particular adaptability handicap as well as a missed opportunity to manage road assets more efficiently and sustainably.

The pavement deterioration process is a stochastic, continuously changing process due to data measurement errors, nonlinear behavior in the pavement deterioration process, and the role of unexplained influencing variables [6]. The measurement of pavement deterioration and its modeling requires complex empirical models to capture it through certain probability distribution functions. The empirical models using traditional statistical regression techniques generally do not consider the stochastic nature of the service life of the pavements deterioration process and cannot explain the uncertainties in the deterioration process [7]. Within the framework of Industry 4.0, the automation of PMS has been of interest to academia and industries [8]. This new trend is known as Smart Pavement Management (SPM), which takes advantage of new hardware tools and information and communication technologies for automatic prediction and data collection, even in real time [9]. Likewise, software tools based on artificial intelligence (AI) integrate and enhance data processing, information analysis, and the subsequent standardization of decision-making concerning the functional service life of infrastructure [10]. ISO15686-1 (2011) define functionality or users' demand as "regarding the description of what stakeholders need in relation to what the building can perform concerning their demand. This concept is defined as level of functionality. Taken together, these levels of functionality form a profile of the requirements of the users and stakeholders".

The synergistic use of PMS with industry inputs that contribute to the technological revolution in the sector will contribute to the accelerated adoption of technologies for general use, which is already having an impact on our direct environment [11]. The massification of data through the use of big data, including data engineering, data analytics, AI, and the Internet of things, among other various technologies, is currently introducing profound changes in society, culture, social bonds, the industry, and specifically for this study, in the application towards the intelligent management of airport road infrastructures [12].

Policies of the Chilean Ministry of Public Works

PMS is usually based on traditional monitoring processes, which largely depend on the experience acquired over time by the entities involved. In this sense, new advances and contributions to the industrial sector are required. The Construye 2025 program unites the public, private, and academic sectors in Chile to work on long-term initiatives to create a more sustainable, productive, and competitive industry [13].

The Ministry of Public Works (MOP in Spanish) and the construction sector agree with the need to implement new methodologies that contribute to the technological revolution of the sector with a focus on digitization [14]. Considering the current Strategic Map of the MOP Airports Directorate, the objective is to contribute to the development of the country and the improvement of people's quality of life through efficient, innovative, transparent, and environmentally friendly airport infrastructure services. In this sense, it should be noted that this particular study specifically focuses on the following items of the Strategic Map of the DAP–MOP [15]: (i) Result 4—Achieve a certain defined level of efficiency in the use of resources; (ii) Integrated Planning 3—Develop coordination processes with other organizations to agree on policies and interventions; (iii) Efficient and Effective Execution 9—Develop efficient infrastructure conservation processes; (iv) Management Quality 14—Implement models and processes for efficient use of resources; (v) Institutional Culture and Learning: Growth and Technology 5—Develop and implement processes that support knowledge management; and (vi) Growth and Technology 6—Strengthen management processes through communication information technologies [14].

2. Research Aim

At a general level, the aim of this study was to make a new contribution to alleviating the challenge of the digital transformation of the industry in pursuit of an increase in the competitiveness of public and private entities and research centers. More specifically, the aim of this study was the development of a new functional service life index focused on Portland cement concrete pavements emplaced in the secondary net of Chilean airports. The case study of this research work is the Viña del Mar Airport located in Concón, Central Chile. The model, which is based on a fuzzy inference system, pretends to generate strategies in terms of effective maintenance actions concerning concrete pavement in use condition.

The innovation of this research work is a digital management tool based on a fuzzy system, which contributes to new intelligent management systems for concrete pavements in Chile through a system based on AI. This approach also makes a new contribution to the incorporation and use of emerging technologies. These advances contribute to the generation of new methodologies that are more efficient, less expensive, safer, and more respectful of the environment.

3. Materials and Method

3.1. Case Study. Airport of Viña del Mar, Valparaíso Region, Chile

The case study selected the Airport of Viña del Mar is located at 32°56′59″ South latitude and 71°28′43″ West longitude, 15 km northeast of the city of Viña del Mar in the Valparaíso Region at an elevation of 140 m. The airport currently has a runway that is 1750 m long by 30 m wide, oriented from southwest to northeast, with thresholds designated 05/23 according to magnetic north. Figure 1 shows a floor plan with the location of the taxiways and the airfield platform.

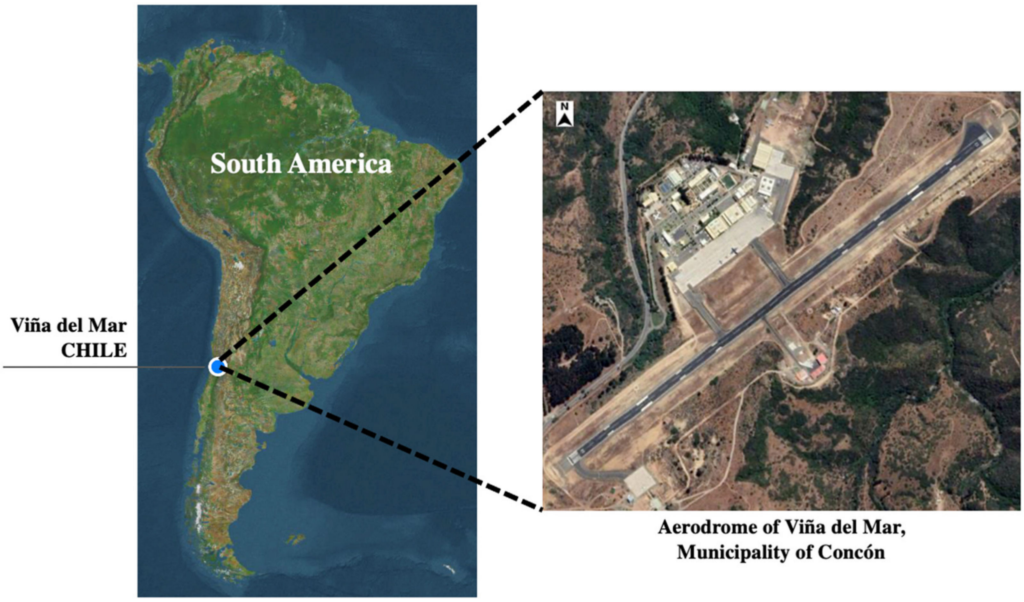

Figure 1. Location of Viña del Mar airport (Valparaíso region, Central Chile).

The airport airside has a total paved surface of approximately 122,361.8 m^2, with the presence of flexible structure pavement (hot mix asphalt) predominating at 68% of the total compared to the rigid pavement (concrete pavement), which is equivalent to 32% [14]. The airport has a flexible structure pavement runway (asphalt) 1750 m long and 30 m wide with 7.5 m wide margins of asphalt irrigation (unpaved). The track has a longitudinal gradient of 0.60%. The Runway, Thresholds, and Jet Protection Zones comprise a paved surface space of 59,678.5 m^2 of a flexible pavement structure (asphalt). The Commercial Platform measures 5765.3 m^2 of a rigid pavement (concrete) without margins [14].

Two military platforms, Military Platform 1 and Military Platform 2 are connected by a shoot called the Military Platform Shoot. Military Platform 1 is comprised of 1083.5 m^2 of flexible pavement (asphalt) and 27,662.2 m^2 of a rigid pavement (concrete) and has a 4-m-wide asphalt margin on the southwest side of the platform. Military Platform 2 is comprised of 819 m^2 of flexible pavement (asphalt) and 5435.9 m^2 of a rigid pavement (concrete) and has 5-m wide asphalt margins. The Military Platform Filming is 137 m long by 18 m wide and has 6 m margins, adding a paved surface of 4080.6 m^2 of flexible pavement (asphalt). The Air Club Platform measures 2298 m^2 of flexible pavement (asphalt) and 864.5 m^2 of a rigid pavement (concrete) [14]. Figure 2 shows a floor plan with the different taxiways and platforms of the Viña del Mar Airport. Table 1 provides a summary of the geometry and materiality of the pavement located in the airport movement area.

Figure 2. Taxiways and platforms of the Viña del Mar Airport.

Table 1. Summary table geometry and materiality of the Viña del Mar Airport movement area.

Sector	Large (m)	Width (m)	Total Area (m^2)	Material
05/23-Landing and take-off runway	1904.29	30	57,128.70	Asphalt
Jet protection zone 05	30.75	40	1229.80	Asphalt
Jet protection zone 23	30.00	44	1320.00	Asphalt
Juliet taxiway	217.73	18	3919.14	Asphalt
Echo taxiway	233.17	18	4197.01	Asphalt
Echo taxi margin	429.87	6	2579.20	Asphalt
Fox taxiway	207.27	18	3730.79	Asphalt
Fox taxi margin	337.85	6	2027.10	Asphalt
Military platform taxiway	148.87	18	2679.59	Asphalt
Military platform taxiway margin	233.50	6	1401.00	Asphalt
Aerial club platform	230.60	6	1383.60	Asphalt
Military platform 1 (PL-2, PL-3, PL-4, PL-5)	355.32	80	27,662.20 m^2 concrete pavements 763.50 m^2 asphalt pavements	Concrete and Asphalt
Military platform 1 margin	80.00	4	320.00	Asphalt
Military platform 2 (PL-7)	60.40	90	5436.00	Concrete

Table 1. *Cont.*

Sector	Large (m)	Width (m)	Total Area (m^2)	Material
Military platform 2 margin	163.80	5	819.00	Asphalt
Commercial platform (PL-1)	72.07	80	5765.60	Concrete
Total Asphalt pavements [m^2]			38,863.80	Concrete
Total Concrete pavements [m^2]			83,498.42	Asphalt

3.2. Fuzzy Logic System for Predicting Concrete Pavement Service Life

Various AI methodologies, including genetic algorithms, fuzzy logic, and artificial neural networks, can predict different real-world phenomena [16,17]. In 1965, Lofti A. Zadeh introduced the fuzzy theory with the relationship of certainty and uncertainty and its many possible applications in different areas [18,19]. In the engineering area, fuzzy logic approaches can be utilized to evaluate various uncertain problems [20]. Fuzzy logic systems have been applied in several industrial process controls [21]. In this sense, fuzzy set methods are accurate computational methodologies for modeling and simulating processes in which the necessary information is not completely available to stakeholders [22].

Fuzzy inference system (FIS) approaches are in line with human thinking and demonstrate the ability to deal with subjectivity, ambiguity, and uncertainty criteria [23]. This kind of method imparts mathematical knowledge and expertise to less-experienced engineers based on a membership degree rather than on a crisp membership of classical binary logic. Researchers who study pavement performance classifications, mainly focused on flexible pavements, have frequently employed this kind of AI technique [24]. Figure 3 presents the main structure of a fuzzy logic system [25]: (i) fuzzification phase, (ii) base of knowledge, (iii) fuzzy inference engine, and (iv) defuzzification phase.

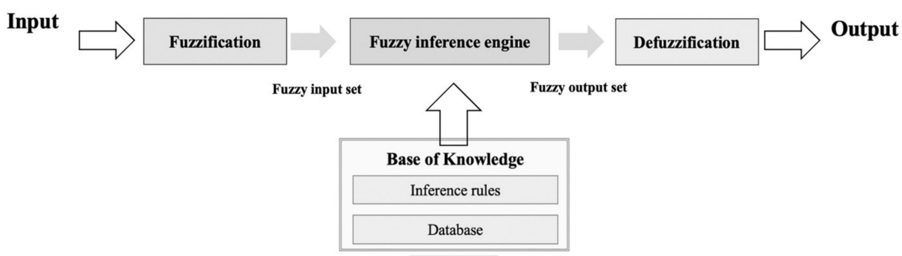

Figure 3. The main structure of a fuzzy inference system (FIS).

3.2.1. Fuzzification Phase

The phase focused on fuzzification facilitates the procedure of transforming a set of crisp values into membership ratings regarding diffuse linguistic terms [26]. The inputs may be turned into linguistic terms, such as (i) 5—very high, 4—high, 3—medium, 2—low, and finally, 1 corresponds to very low. Usually, the membership function (mf) is used to associate a grade with each linguistic term. These methods assign a degree of the membership regarding each element in the universe of discourse U on which the fuzzy set is described [25]. The mf μ_A (u) of a particular fuzzy logic set A can take any possible value from 0 to 1. It is defined in In Equation (1):

$$\mu_A(u) : U \to I[0,1] \quad (1)$$

The fuzzy logic system's FSL-Concrete Pavement index (FSL-CPi) is able to achieve an output focused on the functional service life of concrete pavements concerning a set of three parameters regarding intrinsic vulnerability (I1—cracking, I2—potholes, and I3—raveling) and two external hazards related to atmospheric affections (I4—temperature and I5—rainfall) [27].

The fuzzy logic method focused on the service life prediction of concrete pavement is based on previous experience regarding the functional service life of infrastructures in

Europe (Spain, Portugal) [28,29] and South America (Colombia and Chile) [30,31]. Table 2 describes the quantitative-qualitative input variable valuations. The input parameters of the FIS are fuzzified using Gaussian and Triangular membership functions. These particular MFs were selected to generate the FIS, which is able to predict the functional service life of concrete pavement considering the local context of Central Chile. The input and output variables are associated with different linguistic labels. Figure 4 shows the mfs of the input-output variables. Concerning the type of membership function of each input-output parameter, Jamshidi et al. (2013) state that it depends on the particular problem to be modeled, the experts' knowledge available, and even the particular and specific local contexts of the phenomenon to be predicted [32].

Table 2. Definition of crisp-fuzzy inputs and output variables of the FIS.

Ids	Parameters	Crisp Ratings	Linguistic Term	Membership Function-mf	Fuzzy Ratings	Universe of Discourse (U)
I1	Cracking	1.0 2.0 3.0 4.0 5.0	Very Low (VL) Low (L) Medium (M) High (H) Very High (VH)	mf1-Triangular mf2-Triangular mf3-Triangular mf4-Triangular mf5-Triangular	$1.0 < i1 \leq 2.0$ $1.0 \leq i1 < 3.0$ $2.0 \leq i1 < 4.0$ $3.0 \leq i1 < 5.0$ $4.0 \leq i1 < 5.0$	U_{I1} € (1,5)
I2	Potholes	1.0 2.0 3.0 4.0 5.0	Very Low (VL) Low (L) Medium (M) High (H) Very High (VH)	mf1-Triangular mf2-Triangular mf3-Triangular mf4-Triangular mf5-Triangular	$1.0 < i2 \leq 2.0$ $1.0 \leq i2 < 3.0$ $2.0 \leq i2 < 4.0$ $3.0 \leq i2 < 5.0$ $4.0 \leq i2 < 5.0$	U_{I2} € (1,5)
I3	Ravelling	1.0 2.0 3.0 4.0 5.0	Very Low (VL) Low (L) Medium (M) High (H) Very High (VH)	mf1-Triangular mf2-Triangular mf3-Triangular mf4-Triangular mf5-Triangular	$1.0 < i3 \leq 2.0$ $1.0 \leq i3 < 3.0$ $2.0 \leq i3 < 4.0$ $3.0 \leq i3 < 5.0$ $4.0 \leq i3 < 5.0$	U_{I3} € (1,5)
I4	Temperature	1.0 2.0 3.0 4.0 5.0	Very Low (VL) Low (L) Medium (M) High (H) Very High (VH)	mf1-Triangular mf2-Triangular mf3-Triangular mf4-Triangular mf5-Triangular	$1.0 < i4 \leq 2.0$ $1.0 \leq i4 < 3.0$ $2.0 \leq i4 < 4.0$ $3.0 \leq i4 < 5.0$ $4.0 \leq i4 < 5.0$	U_{I4} € (1,5)
I5	Rainfall	1.0 2.0 3.0 4.0 5.0	Very Low (VL) Low (L) Medium (M) High (H) Very High (VH)	mf1-Triangular mf2-Triangular mf3-Triangular mf4-Triangular mf5-Triangular	$1.0 < i5 \leq 2.0$ $1.0 \leq i5 < 3.0$ $2.0 \leq i5 < 4.0$ $3.0 \leq i5 < 5.0$ $4.0 \leq i5 < 5.0$	U_{I5} € (1,5)
FSL-CPi	Functional service life of Concrete Pavement index	0.0 12.5 25.0 37.5 50.0 62.5 75.0 87.5 100.0	Failed (FLD) Very Very Poor (VVP) Very Poor (VP) Poor (P) Fair (F) Good (G) Very Good (VG) Very Very Good (VVG) Excellent (EXC)	mf1-Triangular mf2-Triangular mf3-Gaussian mf4-Gaussian mf5-Gaussian mf6-Gaussian mf7-Gaussian mf8-Triangular mf9-Triangular	$0.0 < \text{FSL-CPi} \leq 12.5$ $0.0 \leq \text{FSL-CPi} < 25.0$ $0.0 \leq \text{FSL-CPi} < 50.0$ $20.0 \leq \text{FSL-CPi} < 60.0$ $30.0 \leq \text{FSL-CPi} < 75.0$ $40.0 \leq \text{FSL-CPi} < 85.0$ $55.0 \leq \text{FSL-CPi} < 100.0$ $75.0 \leq \text{FSL-CPi} < 100.0$ $87.5 \leq \text{FSL-CPi} < 100.0$	$U_{\text{FSL-CPi}}$ € (0,100)

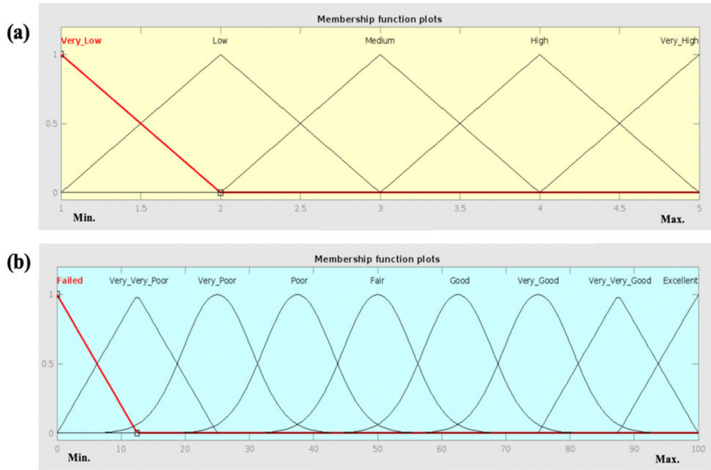

Figure 4. Membership functions of the fuzzy model FSL-CPi: (**a**) inference functions of the input variables (I1–I5); (**b**) inference functions of the output variables (FSL-CPi).

3.2.2. Base of Knowledge and Fuzzy Inference Engine

This stage is defined by Kosko (1994) as the main engine of a FIS [33]. The knowledge base is the key part of a FIS that combines evidence resulting from the phase of fuzzification with the base set of inference rules that were earlier produced and carried out in the modeling procedure. These types of FIS have been widely applied in several engineering and industrial situations [34]. Mamdani is the FIS, which applies a set of fuzzy inference rules supplied by experienced human operators [35]. In a Mamdani FIS [36,37], the consequents of the base set of rules are computed by professional expert opinions and data collection concerning the T-normˆ (minimum) as the usual logic connection 'and' (Equation 2):

$$\mu_A(x) \ and \ \mu_B(x) = MIN\{\mu_A(x), \mu_B(x)\} \tag{2}$$

FIS can be considered a gray-box model because it can define associations by means of IF-AND-THEN rules [38]. This new FIS contains a total of 105 fuzzy inference rules. In Figure 5, a sample of 20 fuzzy IF-AND-THEN inference rules of the FIS implemented in the MATLAB® software package is shown. In Figure 6, the hierarchical structure of the new fuzzy model (FSL-CPi) is shown.

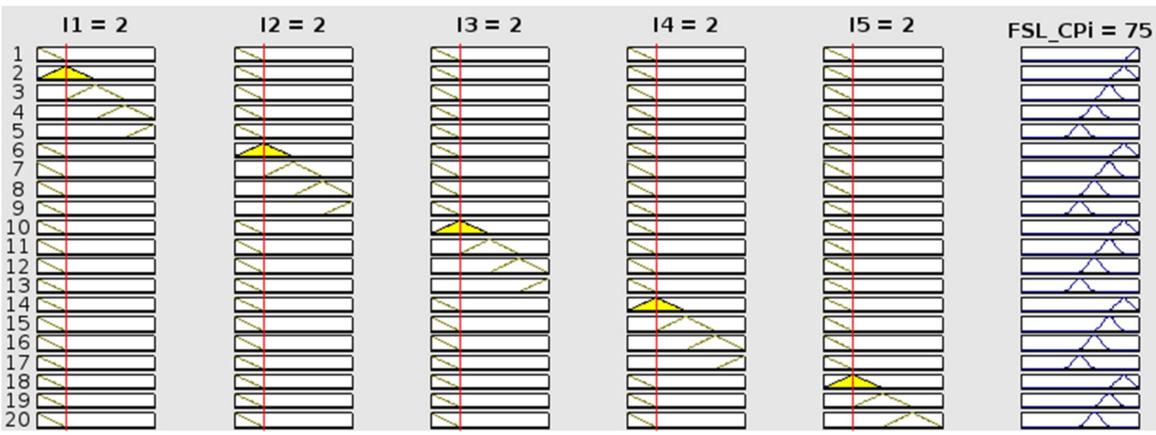

Figure 5. Fuzzy logic reason mechanism.

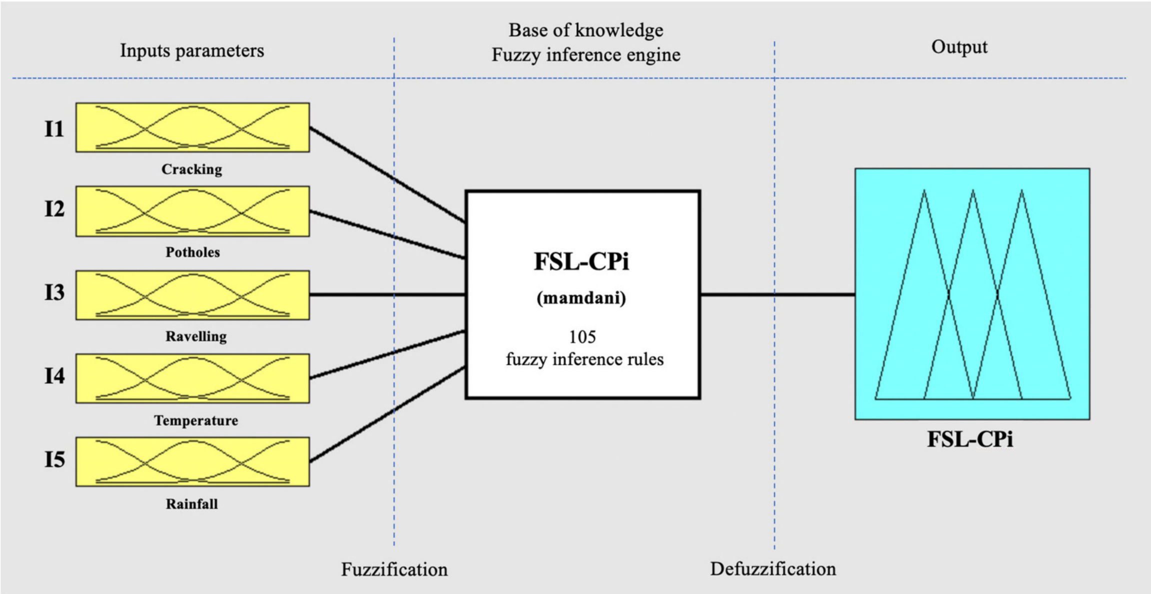

Figure 6. The hierarchical structure of the FSL-CPi fuzzy logic model.

3.2.3. Defuzzification Stage

In the phase of defuzzification, the FIS translates fuzzy sets into crisp values. In the literature, several defuzzifier methodologies are described [39]. One of the most common defuzzification techniques is the center of area (CoA) technique, as described in Equation (3):

$$SL - CPi = \frac{\int_z \mu_A(Z)Zdz}{\int_z \mu_A(Z)dz} \quad (3)$$

where z is the number of discrete arguments of the fuzzy set, and μ_A (z) is the aggregate output MF [40].

Some of the main advantages of the CoA technique is that all active membership functions contribute to the defuzzification process of the FIS [41]. The principal model's output is the FSL-CPi, allowing stakeholders to make decisions concerning a set of horizontal infrastructures (concrete pavements) located in a specific local context. This fuzzy model has been developed considering three functional service life levels according to the ISO31000:2018 [42]: Condition A—The infrastructure presents an adequate functional level. In this situation, the model does not recommend corrective or preventive intervention—only a monitoring survey is recommended; Condition B—Benefits and costs and preventive measures must be taken into account and balanced. A preventive intervention should be considered in a short period of time; and Condition C—The risk is contemplated as an intolerable measure, regarding a very high priority of intervention in a short period of time. A corrective intervention must be considered as soon as possible to preserve the infrastructure.

4. Results

4.1. Definition of the FIS Conditions Focused on Functional Service Life Prediction of Concrete Pavements

For a detailed analysis of the output model (FSL-CPi), a set of nine simulations have been developed. These kinds of fuzzy logic simulations or theoretical approaches are key to realizing the specific performance of the FSL-CPi during the decision-making process [43]. This analysis involved nine simulations, with the input parameters regarding the functional service life of concrete pavements ranging from the minimum (1.0 point) to the maximum (5.0 points). A Likert scale was used in the numerical scale input definition. Table 3 describes the set of theoretical approaches in detail.

Table 3. Fuzzy logic system (FSL-CPi) simulations.

		Simulations				
Parameters		**A**	**B**	**C**	**D**	**E**
Inputs	I1	1.0	2.0	3.0	4.0	5.0
	I2	1.0	2.0	3.0	4.0	5.0
	I3	1.0	2.0	3.0	4.0	5.0
	I4	1.0	2.0	3.0	4.0	5.0
	I5	1.0	2.0	3.0	4.0	5.0
Output	FSL-CPi	96.2	75.0	50.0	25.0	3.9

4.1.1. Simulation A

In the first simulation, (A), all input variables (I1—cracking, I2—potholes, I3—raveling, I4—temperature, and I5—rainfall) were positioned considering the minimum possible valuations (1.0 point: very low valuation). This approach relates to the most favorable situation in which all input factors present the minimum affection to the infrastructure—in this case, concrete pavements. For this approach, the model's output achieved the maximum value in terms of functional service life, which is 96.2 points (Table 3 and Figure 7).

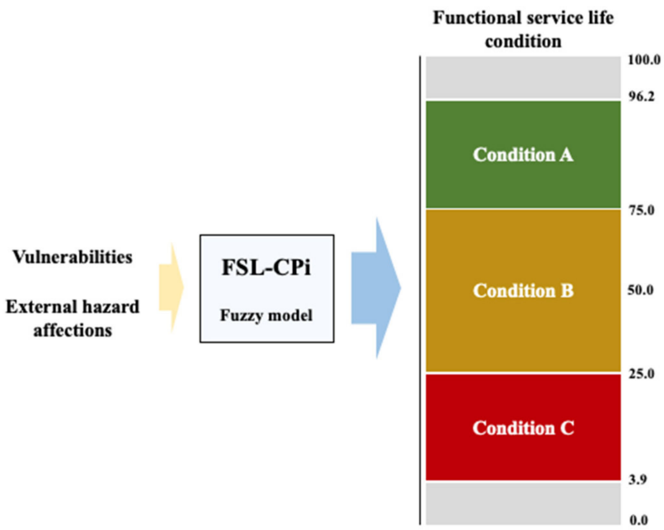

Figure 7. Functional service life range conditions concerning a concrete pavement infrastructure.

4.1.2. Simulation B

In the third simulation, (B), of the FSL-CPi fuzzy model, the five input parameters had 2.0 points (a low assessment—L). In terms of the output value, it was a total of 75.0 points (Table 3 and Figure 7).

4.1.3. Simulation C

In the fifth theoretical approach, (C), the inputs were positioned at 3.0 points (medium valuation—M). In this case, the functional service life of concrete pavements achieved a total of 50.0 points (Table 3 and Figure 7).

4.1.4. Simulation D

The seventh simulation, (D), involves the set of input parameters (I1 to I5) considering a value of 4.0 of 5.0 points. In this case, the functional service life reached 25.0 points (Table 3 and Figure 7).

4.1.5. Simulation E

In the ninth simulation (E), all input parameters (I1—cracking, I2—potholes, I3—raveling, I4—temperature, and I5—rainfall) were situated based on the maximum possible evaluations (5.0 point: very high valuation). This approach relates to the most unfavorable condition in which all inputs have the maximum possible effect on the concrete pavement under analysis. For this approach, the model's output achieves the minimum possible value in terms of functional service life, which is 3.9 points (Table 3 and Figure 7).

Concerning the previous analysis of the fuzzy logic model, the five theoretical simulations assisted in determining the definition of the functional service life ranges specific to concrete pavements. This set of simulations is especially helpful in the analysis process of the real case study (concrete pavements) of the Airport of Viña del Mar (Concón, Valparaíso region, Chile).

The functional service life conditions have been established as follows (Figure 5): (i) Condition A [96.2–75.0]; (ii) Condition B [75.0–50.0]; Condition C [50.0–25.0]; and Condition - D [25.0–3.9] (Figure 7). Currently, the model's minimum sensitivity is 3.9 points, and the model's extremely high sensitivity is 96.2 points. The remaining estimations from 0.0 to 3.9 and from 96.2 to 100.0 will be analyzed in future detailed studies.

4.2. Functional Service Life Correlation Regarding 100 Case Studies

In this subsection, a detailed sensitivity analysis is discussed, which was performed to appreciate the difference and performance of the output—FSL-CPi. The current application determined a set of 100 new case studies, which pretend to be careful in the output analysis of the current version of the model. This application has been designed considering different options in the set of input variables of the FIS to clarify the flexibility of the output model with a focus on the functional service life of concrete pavements. This method contemplates the own vulnerabilities of the infrastructure [25] and the effects of the external hazard, such as atmospheric risks (temperature and precipitations). Several previous approaches have been developed considering vertical infrastructures and analyzing functional service life in relation to intrinsic vulnerability variables and external risks effects [28,44,45].

As Tinga et al. (2021) [46] state, the concept of functional service life is normally meaningless unless different functional requirements and demands are expressed quantitatively [47,48]. Thus, this approach establishes a correlation between functional service life and time-in-service of a set of 100 theoretical case studies. This approach has been developed, such as sensitivity analysis of the new FIS model. Therefore, it is able to provide information to support decision-making and to optimize possible preventive conservation policies for concrete pavements in Chile. After quantifying the different input variables of the model in the FSL-CPi system, a priority classification of the set of 100 theoretical case studies has been achieved. The sensitivity analysis was modeled based on a very low (Condition C) to a very high (Condition A) functional service life (Figure 8).

The set of 100 theoretical samples has been developed using Microsoft Excel. The first case study corresponds to the lowest possible value (1.0 point) of the five inputs. The last application shows the highest possible value (5.0 points) of the five input parameters of the fuzzy model. The remaining 98 cases assessed are a set of arbitrary combinations that assign values from 1.0 to 5.0 for each of the sets of input variables. In this case, a correlation of Pearson's coefficient (r) of 0.9935 was obtained for the 100 theoretical cases developed and applied in this study. The analysis of the determination coefficient (R^2) that estimates the proportion of variance of the x-axis (time estimation in years) related to the y values (functional service life index) demonstrated $R^2 = 0.9872$ based on a lineal curve $y = -1.8268x + 101.42$, which indicates a very high correlation between the variables considered in the theoretical study (functional service life and time estimation in years). Figure 8 illustrates this approach.

This sensitivity analysis between functional service life and time estimation helps to validate the results of the FSL-CPi fuzzy logic model in which the highest functional service life level corresponds to the lowest estimation in terms of time (years), and vice versa, the lowest functional service life level matches the highest estimation of years (Figure 8).

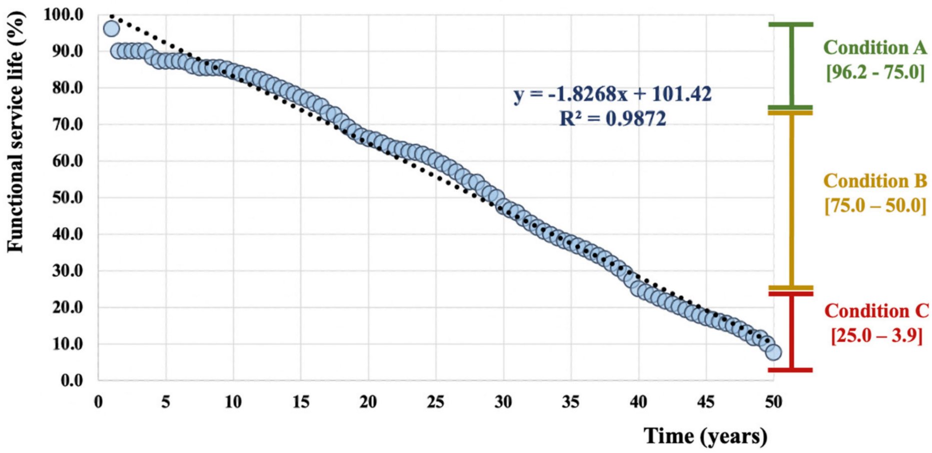

Figure 8. Functional degradation evolution concerning the sensitivity analysis of the FSL-CP index.

The worldwide aim of sustainable development requires informed decision-making processes concerning built environments to ensure an optimum functional service life of available infrastructure. This particular issue depends on the quantification of changes in the conditions of materials over time [49]. In this case study, the functional degradation of concrete pavements in Central Chile, South America, was examined. The creation of more useful computation tools using AI for the development of preventive maintenance plans will help significantly to increase the performance and longevity of different countries' infrastructures [50].

5. Discussion

This subsection considers the practical application of the fuzzy model FSL-CPi to six particular sections of concrete pavements in the airport of Viña del Mar (Concón, Valparaíso region, Chile). Figure 9 shows the particular location of each case study (concrete pavements) in Viña del Mar Airport. It should be mentioned that a total of two parameters are constant in this application: I4-temperature corresponds to 1.9, and I5-rainfall relates to 1.9. This is mainly because the airport was under examination and situated in the same city, considering the similar local background. The remaining three variables (I1-cracking, I2-potholes, I3-ravelling) were evaluated considering an in-situ visual inspection (Figure 10).

The following results were achieved after the application of the fuzzy model FSL-Cpi—output: functional service life of concrete pavements: (i) PL-1 was categorized in Condition A (upper level of concrete pavements functionality) with a total of 82.2% of 92.6; (ii) PL-2 obtained 81.9% of the FSL-CP index, which has been ranked as Condition A; (iii) PL-3 is also classified as Condition A and obtained output of 75.6%, and the worst variable evaluated was I1-cracking with 2.0 points of 5.0 points; (iv) PL-4 and PL-5 obtained an FSL-CPi of 82.0% (Condition A) in both cases; and (v) PL-7 achieved the worst classification with a functional service life index of 49.2%—Condition B (medium level of concrete pavements functionality). Variable I1- cracking was ranked at 4.75 points of 5.0 points, and I2—potholes were rated as a total of 3.5 of 5.0 points. Figure 11 shows the current functional performance of the six case studies analyzed in the Airport e of Viña del Mar, Central Chile.

The results of this functional degradation index (FSL-CPi) analysis and subsequent recommendations can help in providing recommendations for adjusting budgets, saving time, and utilizing professional experts [51]. This kind of digital application helps in the optimization of decision-making procedures for seeking and delivering practical, sustainable solutions for preventive maintenance of vertical and horizontal infrastructures [52]. Concerning the limitations of the study, the FIS (FSL-CPi) model was developed to consider the functional performance of concrete pavements in Chile. Therefore, future applications in contexts inside or outside of Chile with new adaptations to the particular environmental, social, and local frameworks are recommended. It could be recognized as a possible benefit and flexibility of fuzzy logic systems [53].

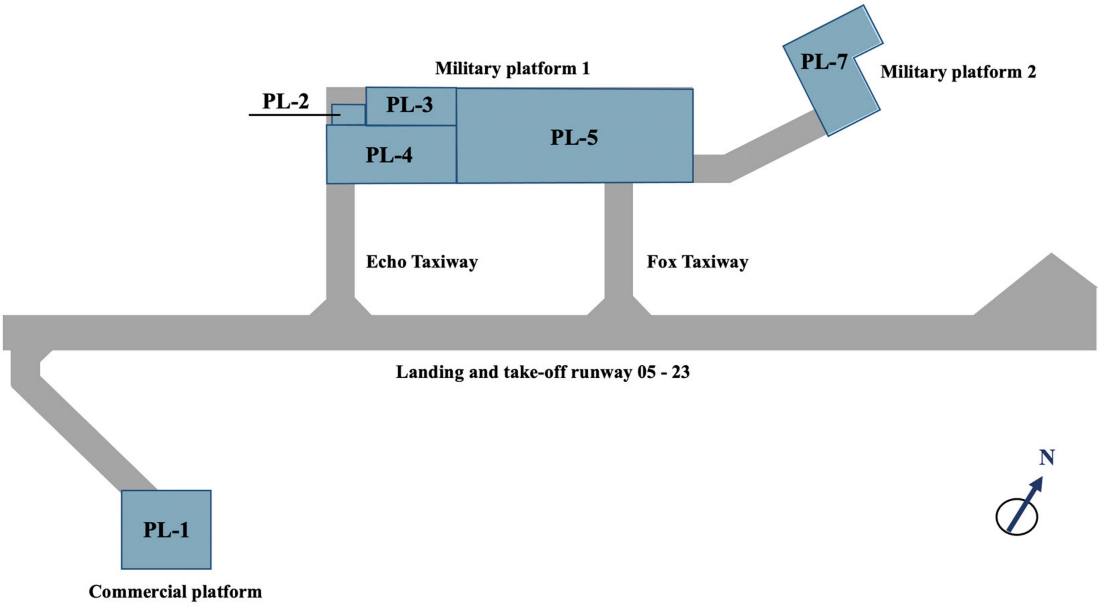

Figure 9. Emplacement of concrete pavements analyzed in the Airport of Viña del Mar.

Figure 10. Deteriorations identified in concrete pavements of Military Platforms (Viña del Mar Airport) during data collection of pavement performance via in-situ visual inspections and automatic inspections via Aerial Unmanned Vehicles (UAVs) or drones.

Location	**ID**	**I1**	**I2**	**I3**	**I4**	**I5**	**FSL-CPi**	**Condition in Sep 2022**	**Pictures**
Commercial platform	PL-1	1.25	1.00	1.00	1.90	1.90	82.2	A	
Military platform 1	PL-2	1.90	1.30	1.30	1.90	1.90	81.9	A	
	PL-3	2.20	1.80	1.50	1.90	1.90	75.6	A	
	PL-4	1.20	1.40	1.70	1.90	1.90	82.0	A	
	PL-5	1.70	1.20	1.20	1.90	1.90	82.0	A	
Military platform 2	PL-7	4.75	3.50	1.60	1.90	1.90	49.2	B	

Figure 11. Application of the fuzzy logic system (FSL-CPi) to the concrete pavement case studies emplaced in the Viña del Mar Airport.

6. Conclusions and Future Research Work

A new methodology has been developed based on innovative policies (AI) to preserve public infrastructures, such as the concrete pavements of the airports managed by the Ministry of Public Works, Government of Chile. This kind of method can contribute to cost minimization and benefit optimization in the local context. This service life prediction model based on FIS supports new policies for the recovery and protection of Chilean infrastructures and will contribute to the MOP principles, which aim to provide a new approach to the progress of the country and the improvement of the quality of life of the people through efficient, innovative, transparent, environmentally sustainable, and forward-thinking airport infrastructure services. In this respect, the new digital model FSL- concerns the FIS package of MATLAB® software, which is an innovative tool of applied technology in Latin America (Chile). Concerning the case analyzed, commercial platform and military platform 1 presented: Condition A—Risk is regarded as negligible, and the infrastructure presents an adequate functional level. In this situation, the model does not recommend corrective or preventive intervention—only a monitoring survey is recommended. However, Military platform 2 presented a higher level of functional service life deterioration. Condition B—Costs and benefits of preventive measures must be taken into account and balanced. Preventive intervention should be considered in a short period of time.

Regarding the limits of annual budgets around 540,000 USD for the diagnostic and conservation of pavement maintenance plans. However, one must select ranked sections for an ideal maintainability procedure. The digital fuzzy logic system regards the joint effect of important factors, such as the functional degradation of pavement. Because prioritization is a decision-making process, statistical models are not highly responsive. Therefore, engineers and public administrators must use more accurate decision-making processes to predict real-world phenomena considering less uncertainty. This digital fuzzy logic model presents the ability to implement different kinds of information, such as pictures or videos from inspection stages considering maintenance actions, and to arrange automatized decision-making for a specific issue.

The main advantage to the international community is the opportunity of overseeing an unrestricted quantity of pavement using a multicriteria decision-making process, which is based on the functional service life of the infrastructure under analysis; however, currently, the model FSL-CPi can only implement information from professional experts obtained from in-situ visual inspections. In future research, new developments and applications of the system will need specific adaptations with a new version of the system. Digital methods may also be modified to new possible situations in sociocultural, environmental, and natural contexts.

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