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AI-based Decision Support System for Heritage Aircraft Corrosion Prevention

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***Abstract*—The paper presents a decision support system for the long-term preservation of aeronautical heritage exhibited/stored in sheltered sites. The aeronautical heritage is characterized by diverse materials of which this heritage is constituted. Heritage aircraft are made of ancient aluminum alloys, (ply)wood, and particularly fabrics. The decision support system (DSS) designed, starting from a conceptual model, is knowledge-based on degradation/corrosion mechanisms of prevailing materials of aeronautical heritage. In the case of historical aircraft wooden parts, this knowledge base is continuously filled in by the damage function models developed within former European projects. Model-based corrosion prediction is implemented within the new DSS for ancient aluminum alloys. The novelty of this DSS consists of supporting multi-material heritage protection and tailoring to peculiarities of aircraft exhibition/storage hangars and the needs of aviation museums. The novel DSS is tested on WWII aircraft heritage exhibited in the Aviation Museum Kbely, Military History Institute Prague, Czech Republic.**

***Index Terms*—decision support system, aeronautical heritage, preventive approach, corrosion prediction, ancient aluminum alloys, machine learning**

I. Introduction

Nowadays, a decision support system (DSS) becomes a tool for on-time and adequate safeguarding of the heritage in its complexity. The DSS regularly includes retrofit or refurbishment measures of historic buildings/sites, and the natural goals of all the measures recommended/assigned by the DSS are an extension of the heritage lifetime and an improvement of the energy efficiency and the environmental performance, as detailed in [1]. Another of these measures is the removal of the collection safety threats, for instance, textile carpets due to the resuspension; for more details on visitor-triggered resuspension, see [2]. Common approach to safeguarding the heritage, see recent studies [1], [3], [4], relies on risk-based analysis for supporting a decision-making process on heritage conservation, energy efficiency, and visitor/staff comfort in historical buildings. This risk-based analysis is a multidisciplinary task involving physics, computer science, and information technologies (IT).

In [1], SOBANE (screening, observation, analysis, expertise) methodology is applied to developing the DSS that utilizes identified heritage damage sensitivities and the environmental requirements for guaranteeing its conservation and management, considering the opposite needs of conservation and human comfort. In [5], the DSS called ArcheoRisk is developed to safeguard/rehabilitate archaeological sites in Venice Lagoon. Thereby, the archaeological risk evaluation and intervention selection is underpinned by the Geographical Information System (GIS) platform. In [6], E-Museum is developed to provide advanced services utilizing a Wireless Sensor Network (WSN) to collect real-time monitored data to facilitate the management of museum activities. While in [7], the DSS is dedicated to optimizing visitor flows functionally to designing prospective exhibitions. In [4], enhanced usage of artificial intelligence (AI) enabled the achievement of decision-making tools based on machine learning via thermo-hygrometric and energy simulations of different scenarios for museums' use and management. However, AI-based risk analysis requires a large amount of data available for supervised training at best. Since these data are missing or lacking, the synthetic data are being

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obtained by numerical simulations instead; for more details, see [4]. On the other hand, the digital cultural heritage, also linked to AI capability, is due to visitor facilitation, disasters, armed conflicts, etc., an important matter of interest among all the actors in cultural heritage preservation, [8]. In [9], *MiCorr* Decision Support System is developed within the MIFAC Metal project to diagnose the corrosion forms of heritage metals and to decide on conservation protocols (thus, to find treatment protocols). Furthermore, to get corrosion models of historical and archaeological artifacts, the MIFAC Metal case studies, see [9] and references therein, were applied to develop the *MiCorr* DSS.

The conservation status of aeronautical heritage has been mapped years ago [10]–[13]. The heritage aircraft are composed of sandwich structures made of parts of aluminum alloys, wood (plywood. balsa), and fabrics (textile, canvas), in particular, [14]. These materials degradate/corrode in various ways, as reported in [15], [16], and [17], and referred in [10]–[13]. Aside from material degradation/corrosion problems, the heritage aircraft hangars are deficient in equipment (e.g., HVAC) and insulation (shell buffering), as a rule. There are only a few studies coping with the protection of this heritage type [10], [13], [18], [19], but the earliest study on the protection of "ancient" aluminum alloys deployed in pre-war aircraft was presented already in 1934, [20]. Very recently, a comprehensive study on a preventive approach to aircraft heritage protection has been carried out in [21]. Viewing the state-of-the-art above in the aeronautical heritage protection a novel DSS being developed and presented in this paper is tailored to the preventive approach from [21], with prospective intention of DSS's adaptability to different heritage sites.

II. Design and implementation of decision support system

First of all, a conceptual model is achieved in a DSS development to represent the knowledge base and to model the semantic data. The conceptual model is translated into a data structure and finalized into a visual outcome to work on a DSS and provide a linkage between reality and the data structure. The outcome is then a visual representation of the decision-making process (reasonings of actions to undertake) in favor of aeronautical heritage preservation as described in the DSS design below.

The DSS design for preserving aeronautical heritage is based on multiple-input and multiple-output (MIMO) decision tree model. The learning of a decision tree was chosen because we consider it desirable to design the DSS as data-driven due to the possible complexity of all input-output combinations rather than hardcoding all of the rules. However, the input-output combinations for learning were defined by experts or by literature knowledge at the first step. Adaptability is a cornerstone of this system's design. Upon introducing new input-output data, the decision tree requires retraining to assimilate the fresh data, thereby maintaining the accuracy and relevancy of its recommendations. The system's input and output structure are presented in tabular forms (Tab. I, Tab. II). The DSS architecture in Fig. 1 shows a comprehensive framework, integrating external and local environmental data sources, storing them in the database, and using state-of-the-art frameworks.

Online data acquisition is a crucial system component, utilizing METAR (Meteorological Terminal Air Report) reports [22] to harvest real-time meteorological data, including air temperature, dew point, wind speed and direction, and general weather conditions. The Czech Hydrometeorological Institute (CHMI) data extends the system with localized pollutant concentrations, including SO_2, NO_2, CO, O_3, PM_{10}, and $PM_{2.5}$ levels. Complementing these datasets, local measurements from indoor ambient data provide crucial parameters such as indoor air temperature, humidity, and, if available, particulate matter and volatile organic compound (VOC) concentrations.

In tandem, the server employs a data-driven corrosion model obtained with the *pycaret* framework, [23], utilizing experimental data to evaluate corrosion risks. The model interprets ambient conditions, including air temperature, humidity, and pollutant levels, to calculate a risk score that quantifies the potential for corrosion. This approach uses the data-driven corrosion modeling from [21].

The fusion of experimental and literature data, predefined infiltration thresholds, and data-driven corrosion models empowers the DSS to deliver decisions catering to the nuanced needs of heritage aircraft preservation within the variable conditions of storage and exhibition environments.

The DSS is a complex software system that integrates state-of-the-art frameworks such as Scikit-learn, [24], Pycaret, FastAPI to address the non-conventional use case of corrosion prediction in hangars

A Human-Machine Interface (HMI) is developed with Vue.js for user interaction. Through HMI, users will input data described in Tab. I using forms, which the DSS uses to generate corrosion risk estimation and actionable preservation recommendations.

A. Used technologies

As mentioned before, the development of our DSS, called *SmartHangar*, incorporates multiple frameworks. Below, we detail and justify the selection of each tool within our technology stack.

PostgreSQL: Our choice for the database management system is PostgreSQL due to its strong reputation for data integrity and its support for advanced data types. Its robust feature set, including complex queries, extensible indexing, and concurrency without read locks, makes it an ideal choice for managing the complex and relational data structures that DSS *SmartHangar* requires.

FastAPI: FastAPI is employed to create a modern, fast (high-performance) web framework for building APIs. It is selected for its speed, ease of use, and robustness. Its ability to handle asynchronous requests ensures our system can manage a high volume of requests efficiently, which is crucial for real-time data processing and responsiveness.

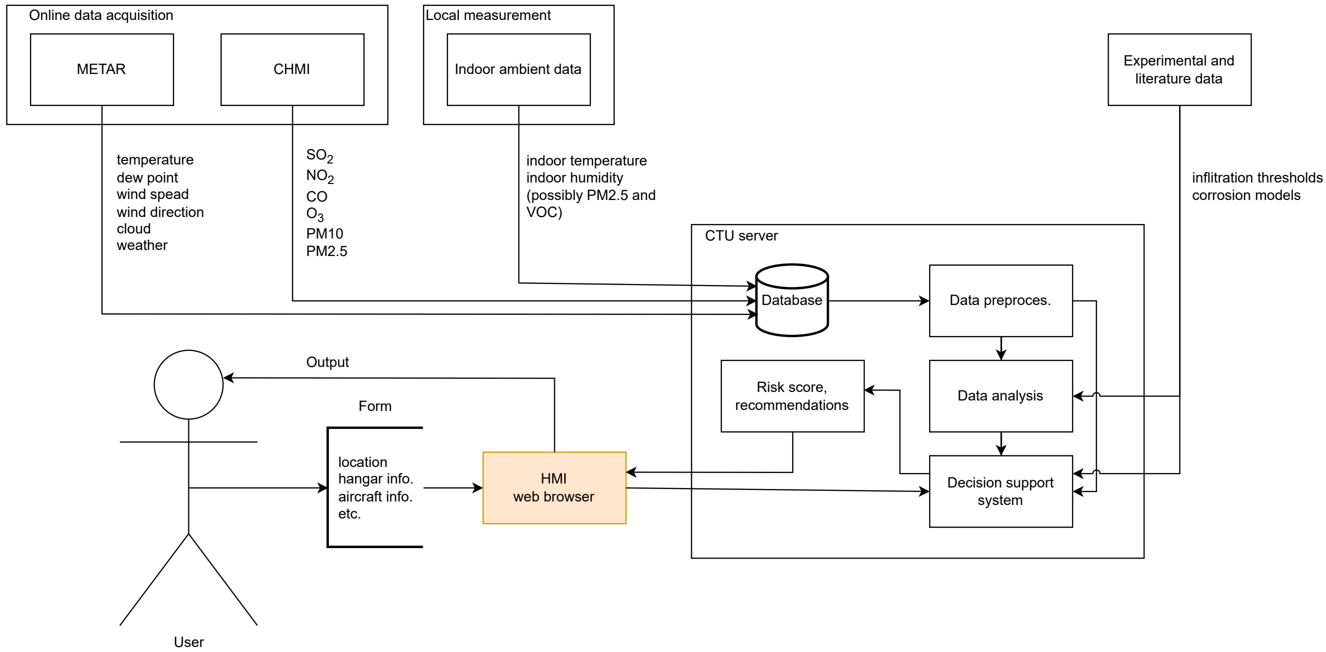

Fig. 1. Architecture of decision support system *SmartHangar*

TABLE I
INPUT FEATURES

Ambient features	**Data type**
Indoor air humidity [%]	Time series
Outdoor air humidity[%]	Time series
Indoor air temperature [°C]	Time series
Outdoor air temperature [°C]	Time series
Indoor dew point [°C]	Time series
Outdoor dew point [°C]	Time series
Outdoor SO_2 [$\mu g\,m^{-3}$]	Time series
Outdoor $PM_{2.5}$ [$\mu g\,m^{-3}$]	Time series
Outdoor PM_{10} [$\mu g\,m^{-3}$]	Time series
Wind speed [$m\,s^{-1}$]	Time series
Air exchange rate [h^{-1}]	Time series
Calculated features	**Data type**
Indoor SO_2 [$\mu g\,m^{-3}$]	Time series
Time of wetness [h]	Numeric
Hangar information	**Data type**
Location near sea {yes, no}	Binary
AC installed {yes, no}	Binary
Heating installed {yes, no}	Binary
Filters installed {yes, no}	Binary
Insulation installed {yes, no}	Binary
Barriers installed {yes, no}	Binary
Carpets installed {yes, no}	Binary
Walls material {wood, steel, concrete}	Categorical
Walls area [m^2]	Numeric
Roof material {wood, steel, concrete}	Categorical
Roof area [m^2]	Numeric
Floor material {wood, steel, concrete}	Categorical
Floor area [m^2]	Numeric
Exhibition area [m^2]	Numeric
Hangar volume [m^3]	Numeric

TABLE II
POSSIBLE ACTIONS

Possible actions
Increase or decrease air exchange rate
Start or stop heating
Start or stop AC
Increase or decrease number of people in the hangar
Change the ratio between exhibition area and hangar volume
Refurbishment
Install filters (HEPA, carbon etc.)
Install AC
Install heating
Install insulation
Install barriers
Uninstall carpets

PyCaret: In building our predictive models, PyCaret offers a low-code machine learning library in Python that automates model training and evaluation. It streamlines the workflow, which enables us to iterate rapidly through different models and preprocessing techniques. Its simplicity and integration with other libraries offer the flexibility needed in a research-oriented development environment.

Scikit-learn: The backbone of our machine learning capability is formed by Scikit-learn. This open-source tool is used to implement the MIMO decision tree model. The library is renowned for its broad range of algorithms, consistent programming interface, and comprehensive documentation, which significantly expedite the development process.

Vue.js for HMI Development: The Human-Machine Interface (HMI) of our system is now being developed using Vue.js, a progressive JavaScript framework. Vue.js is specifically chosen for its simplicity, detailed documentation, and flexibility. It allows for building a reactive, component-driven UI for our DSS, ensuring an intuitive and smooth user experience. Its modular architecture facilitates easy maintenance and the iterative development of the HMI as user requirements evolve.

The integration of these technologies results in a DSS that is functional, adaptable, and easy to update as requirements evolve. The chosen tools enable efficient corrosion prediction, supporting the preservation of aeronautical heritage.

B. Preprocessing

Before analysis, resampling was applied to standardize the temporal resolution across disparate data sources. Linear interpolation was used to fill gaps between existing observations, ensuring all datasets were aligned to a uniform date-time format. This step was essential for synchronizing datasets with varying acquisition frequencies and enabling coherent aggregation.

After resampling, moving average (MA) filters were applied to smooth the time series data, reducing short-term fluctuations and highlighting underlying trends. The sliding window size of the MA filter was a key parameter influencing the accuracy of the corrosion model. The optimal window length was determined through a grid search over values ranging from 1 to 168 hours.

C. Calculated features

The preprocessing pipeline also includes the computation of derived features. One key feature is the Time of Wetness, defined as the total number of hours when relative humidity (RH) exceeds 80 % and temperature remains above 0°C. This parameter serves as an indicator of corrosion risk in the hangar.

Another important feature is indoor pollution concentration, estimated using outdoor pollution levels, the air exchange rate (n), and the materials of both the hangar and stored artifacts. This calculation accounts for pollutant infiltration and interaction with the indoor environment, providing insight into conservation conditions.

These computed features (see Tab. I) enhance the dataset and directly inform the DSS's recommendations for corrosion prevention.

D. Corrosion model

As mentioned in Sec. I, we developed the corrosion model based on the Extra Trees regressor [21]. After performing correlation analysis, the final selected features included the following magnitudes: indoor temperature, indoor humidity, concentration of $\mathrm{SO_2}$, concentration of $\mathrm{PM_{10}}$, concentration of $\mathrm{PM_{2.5}}$, and wind speed. The model was trained and validated using data from the Aviation Museum Kbely, achieving an R^2 score of 0.91. The training was conducted on one year data, while validation was performed using a 25-day hold-out prediction set. We used the configuration with 100 estimators and no limit on tree depth.

E. Risk evaluation

As mentioned in section II and as it is shown in Fig. 2, the first fundamental tool for corrosion risk evaluation is a data-driven corrosion model, which evaluates mainly ambient data, including dew point (DP) temperature. However, we also use the ISO 9223 standard for corrosivity risk evaluation as described in [25], which considers the Time of Wetness and pollution infiltration. Finally, additional rules, such as proximity to the sea or missing building insulation, are used. These parameters are evaluated within the DSS only as input for the decision tree.

III. Use Case

The use case of DSS *SmartHangar* is applied to the Aviation Museum Kbely. Measured ambient data are visualized in Fig. 2 and pollution data in Fig. 3. These data were published in [21]. The rest of input data are described in Tab. III.

As visible in Fig. 2, the output of the data-driven corrosion model predicts high corrosion risk at the end of December, which corresponds with high humidity and temperature jump from freezing to temperatures above zero.

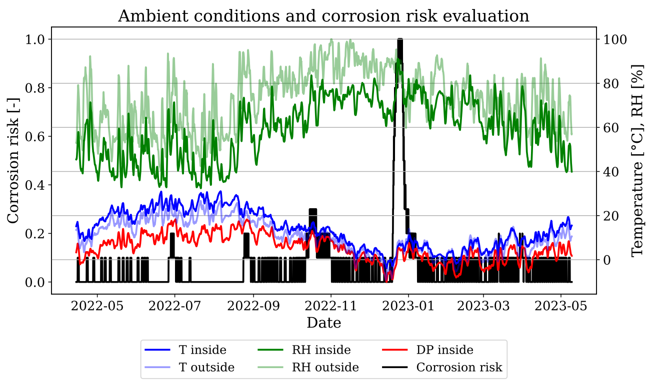

Fig. 2. Measured one-year data and corrosion risk score evaluated.

TABLE III
INPUT FEATURES - USE CASE

Calculated features	**Value**
Time of wetness [h]	60.6
Hangar information	**Value**
Location near sea {yes, no}	No
AC installed {yes, no}	No
Heating installed {yes, no}	No
Filters installed {yes, no}	No
Insulation installed {yes, no}	No
Barriers installed {yes, no}	No
Carpets installed {yes, no}	Yes
Walls material {wood, steel, concrete}	Wood
Walls area [m^2]	1004.8
Roof material {wood, steel, concrete}	Steel
Roof area [m^2]	985.6
Floor material {wood, steel, concrete}	Concrete
Floor area [m^2]	985.6
Exhibition area [m^2]	985.6
Hangar volume [m^3]	7884.8

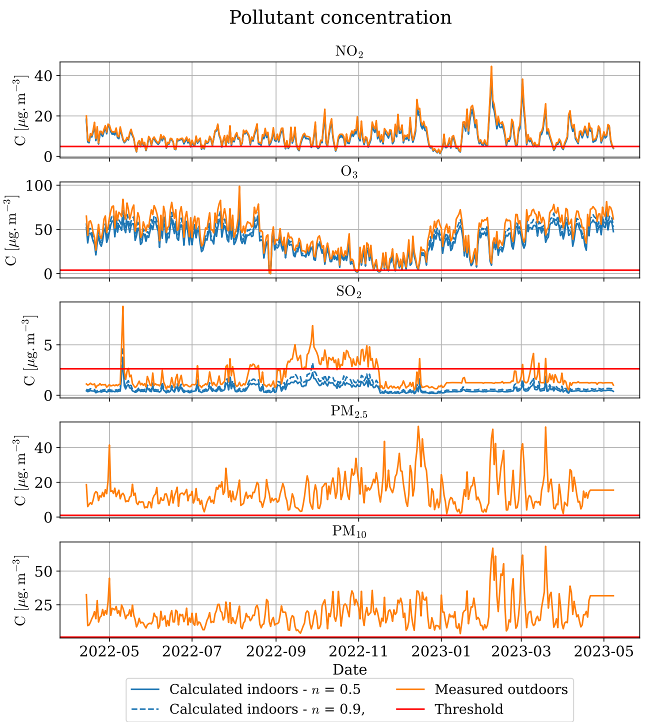

Fig. 3. One-year pollution data measured from weather stations in Prague-Holesovice and Prague-Riegrovy sady and indoor pollution calculated for min-max air exchange rate - Daily averages [21].

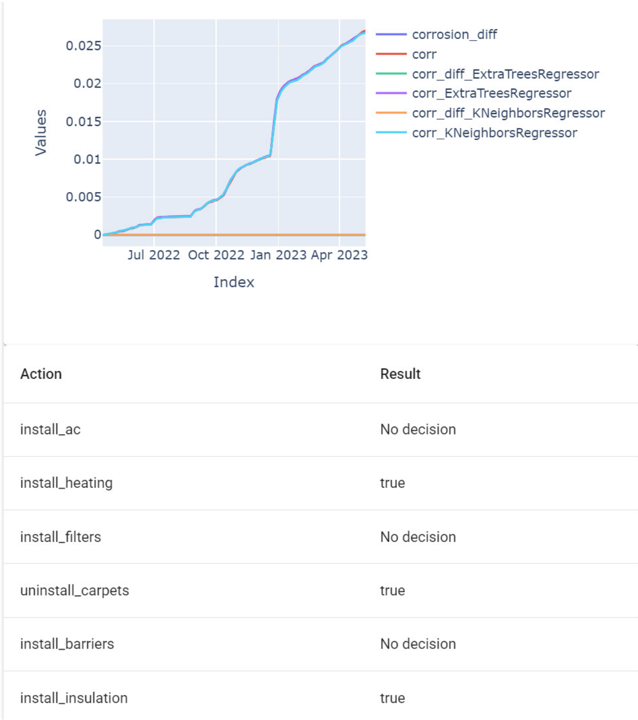

Fig. 4. Screenshot of the results part in HMI of *SmartHangar*.

The output of DSS *SmartHangar* is shown in Tab. IV.

TABLE IV
OUTPUT OF DSS *SmartHangar*

Actions	Output
Increase or decrease air exchange rate	No action
Start or stop heating	No action
Start or stop AC	No action
Increase or decrease number of people in the hangar	No action
Change the ratio between exhibition area and hangar volume	No action
Refurbishment	Output
Install filters (HEPA, carbon etc.)	No action
Install AC	No action
Install heating	Yes
Install insulation	Yes
Install barriers	No action
Uninstall carpets	Yes

The corrosivity category by ISO 9223 standard is C_2 - low (indoor climates without microclimate control like storages).

A partial demonstration of the DSS results in a web browser is shown in Fig. 4.

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CONCLUSIONS

A novel decision support system is developed to preserve aeronautical heritage sheltered in hangars. After processing all the input features (external and internal) and applying the decision tree model, the output features (actions and risk scores) are obtained, providing recommendations for aeronautical heritage preservation. The proposed DSS's use case demonstrates its function in favor of aircraft heritage protection. Other use cases are needed to test the designed DSS on aviation museums located in different geographical locations.

DATA AND CODE AVAILABILITY

The datasets used in this study are available at the Zenodo repository: https://zenodo.org/records/10640939, and the corresponding trained models can be accessed via the GitHub repository: https://github.com/CVUT-FS-12110/Procraft_Corrosion_Model.

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