SÃO PAULO STATE UNIVERSITY SCHOOL OF ENGINEERING OF ILHA SOLTEIRA

NEURAL NETWORKS: ENHANCING INTELLIGENT SYSTEMS WITH DEEP LEARNING

Gabriel D. Silva

Student

Douglas D. Bueno

Advisor

UNESP

Ilha Solteira – SP

2023

RESEARCH REPORT

The present report approaches a way to improve smart systems. Through artificial intelli-

gence applied in the mechanical engineering field, it provides a consistent algorithm that

can reads data, trains the machine and provides results about the situation and what to do

with it. It will be studied two cases, one of them using machine learning classical techniques

to determine the forces applied to a unnamed aerial vehicle and other using deep learning

techniques like neural networks in the structural health monitoring area.

Complete after the research is done.

Keywords: machine learning, structural health monitoring, unnamed aerial vehicle

LIST OF FIGURES

Figure 2.1.1	SHM and Human Nervous System Analogy	4
Figure 2.2.1	Quadcopter Dynamic Scheme	8
Figure 2.3.1	Visual Representation of a MLP	11
Figure 2.3.2	Convolutional Neural Network	13
Figure 2.3.3	Loss Function for Linear Regression	14
Figure 2.3.4	Gradient Descent Process	15
Figure 4.1.1	Loss function to the first model	22
Figure 4.1.2	Comparing the first model with the script	24
Figure 4.1.3	Comparing the second model with the script	25
Figure 4.1.4	Loss function to the second model	26

LIST OF TABLES

Table 3.2.1	Data generation for the Unnamed Aerial Vehicle (UAV)	19
Table 3.2.2	Modeling parameters	20
Table 4.1.1	Model summary	21
Table 4.1.2	Normalized model summary	23

LIST OF ACRONYM

AI Artificial Intelligence

ANN Artificial Neural Network

BD Big Data

CNN Convolutional Neural Network

DL Deep Learning

FEM Finite Element Method

IoT Internet of Things

MEMS Micro Electromechanical Systems

ML Machine Learning

MLP Multilayer Perceptron

MSE Mean Squared Error

NN Neural Network

RNN Recurrent Neural Network

SGD Stochastic Gradient Descent

SHM Structural Health Monitoring

UAV Unnamed Aerial Vehicle

CONTENTS

LIST C	OF FIGURES	ii
LIST C	OF TABLES	iii
LIST C	DF ACRONYM	iv
1	INTRODUCTION	1
1.1	MOTIVATION	2
1.2	OBJECTIVE	2
2	LITERATURE REVIEW	3
2.1	STRUCTURAL HEALTH MONITORING	3
2.1.1	Definition	3
2.1.2	Brief History	3
2.1.3	Main Techniques	5
2.1.4	Railway Cracks	6
2.2	UNNAMED AERIAL VEHICLE CONTROL	7
2.2.1	Usage	7
2.2.2	Motion Equation	8
2.2.3	Control Algorithm	9
2.3	ARTIFICIAL NEURAL NETWORKS	9
2.3.1	Deep Learning	9
2.3.2	Neural Networks Models	10
2.3.3	Loss Function	13
2.3.4	Optimizer	14

3	METHODOLOGY	18
3.1	SOFTWARES	18
3.1.1	MATLAB®	18
3.1.2	TensorFlow	18
3.2	NEURAL NETWORK FOR UAV CONTROL	18
3.2.1	Data Generation	18
3.2.2	Modeling the Neural Network with TensorFlow	20
4	RESULTS AND DISCUSSION	21
4.1	CASE STUDY 1: UNNAMED AERIAL VEHICLE	21
4.1.1	First Model	21
4.1.2	Second Model	22
4.2	CASE STUDY 2: STRUCTURAL HEALTH MONITORING	23
5	CONCLUSION	27
REFER	ENCES	27

1 INTRODUCTION

The use of Artificial Intelligence (AI) is very present nowadays (41, 55, 57). This area of statistics neither is new nor started just now with the autonomous cars and voice assistants (50), but it is clear that in the last years it has been increasingly gaining more popularity. This happens mainly because of the advances that the World Wide Web has been had over the years (42, 15), since dial-up internet connection, back in the eighties, until now, with broadband internet and smartphones equipped with 5G connection. Another factor is that in the past, the cost to get a large capacity of storage memory was significantly more expensive than it is now, what makes today cheaper and easy to get memory to store information (28). With the amount of data available, the evolution of internet and storage capacity, now it is not difficult to obtain, keep and analyze databases to make decisions (21).

AI application is everywhere and today, more than ever, it is easy to realize that. Either to get multimedia recommendations on streaming platforms, like occurs at Netflix, YouTube, Spotify, and so many others platforms (14), or to make predictions on the financial market and sports betting (49, 38, 33), AI is there behind the scenes making all the magic happen. Evidently there is nothing really magical about them, it is pure mathematics combined with a programming language that produces the algorithm capable of doing those things (29, 4, 59, 60). The launch of ChatGPT–3, and shortly thereafter ChatGPT–4, has shown the power of those technologies and how they can change the way people do things (10, 11, 44, 7).

Getting into the smart systems application, the use of AI is widely used to Structural Health Monitoring (SHM), which is heavily used in the aerospace and civil fields, (6, 79). The level and the complexity of the AI to be applied to monitor the structure, whether is going to use Deep Learning (DL) and Neural Network (NN) or simpler methods of Machine Learning (ML) like regressions, is determined by the problem itself and the results desired (23). In some cases, the standards methods use numerical techniques and they may not be feasible, especially when there is a huge data to be analyzed. Thus, taking the AI road is an alternative to get the needed results for the monitoring in a more practical way (67, 70).

Still in this context, but in the field of UAV, the use of AI can be combined to integrate

UAV through wireless communication networks (40) what can be useful in the agriculture sphere (2) with technologies like Internet of Things (IoT) (75, 74). Also, the use of the AI can be subtle, such as the use of a built-in MATLAB® function to make a simple NN to determine the final pose of a UAV based on the initial pose and the forces applied on it (26), or can be more sophisticated, like the use of ML and DL algorithms to predict materials properties, design new materials, discover new mechanisms and control real dynamic systems (31, 3).

It is clear, therefore, that AI can transit into different fields, such as entertainment, business, health care, marketing, financial, agriculture, engineering, among others (61, 80, 19, 76, 48, 53, 27). The use of the Big Data (BD) can not only make it clear the scenario to be studied, but also to support making strategical decisions (34, 39). The internet and hardware improvement (8), alongside the facility to storage data with accessible costs, encourages the AI use due to the benefits it can provide.

1.1 Motivation

- use of AI in (mechanical) engineering
- the problem of shm to use ai
- the problem of vant to use ai
- conclusion

1.2 Objective

To develop an AI algorithm based on NN to apply in smart systems. The main goals are:

- to determine the forces used to move an UAV based on its initial and final pose;
- to detect railways cracks through piezoelectric signal for SHM.

2 LITERATURE REVIEW

This chapter deals with the history, the main concepts and some practical cases of SHM inside the industry and academic area, besides showing how it may be used in the railway crack detection context. Next, in the dynamic field, it will be studied the main mechanical concepts to get the necessary understanding to an UAV motion as well the basics to know how an UAV can be controlled. Then, it will be shown the mathematics behind the algorithms of deep learning that will be implemented in the Chapter 4. Finally, the way how the algorithms are going to be implemented and the tools necessary to achieve the desired neural network.

2.1 Structural Health Monitoring

2.1.1 Definition

According to Balageas; Fritzen; Güemes (9), the SHM main purpose is to provide, during the life of a structure, a diagnosis of: the state of the constituent material; the different parts of the structure; and the full assembly of each part that makes the structure as a whole. It is an improved way to make non-destructive evaluation. It can be applied in several areas such as civil infrastructure, like bridges and buildings; aerospace, like airplanes and spaceships; and mechanical, like machines.

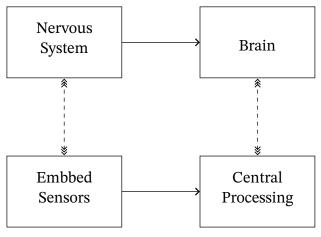
Furthermore, it also can be associated as an analogy to the human nervous system. Just like the sensors send a signal to the central processor, the human senses send a signal to the brain to make the recognition of what is happening, as shown in the Fig. 2.1.1.

2.1.2 Brief History

The SHM development began back in the 20th century and it has been coupled with the evolution of the digital computing hardware, what allowed the costs of the applied techniques less expensive over time.

It all starts back in the early 1970s and 1980s. The oil industry tried to develop vibration-based damage identification methods for offshore platforms by simulating damage

Figure 2.1.1. SHM and Human Nervous System Analogy. The nerve endings are responsible to pass the information to the brain; as the sensors embedded in the structure play the role of the nerve endings, the central processing does the brain role.



scenarios, examining the changes in the resonant frequencies and correlating them with those measured on a platform. In the same period, the aerospace community studied vibration-based damage identification along with the development of the space shuttle. From that, it was developed the shuttle modal inspection system which aimed to identify fatigue damage in components like fuselage panels and control surfaces. The system was so successful that all orbiter vehicles had been periodically subjected to this test. Also, the civil engineering community studied vibration-based damage evaluation of bridge structures and buildings in the late 1980s (22).

From the late 1990s to the early 2000s, Sohn et al. (68) showed the evolution of the techniques used in SHM, analyzing mainly the following factors: the operational evaluation; data acquisition and cleansing; feature extraction; and statistical modeling for feature discrimination. He also verified that the statistical patter recognition had not been embraced by the researchers to be more often used in such matter.

Nowadays, in order to contour inherent issues of SHM methods, as large computational effort and hand-crafted work that results in poor classification performance, many deep learning techniques have been used, such as Convolutional Neural Network (CNN) (5).

2.1.3 Main Techniques

Accelerometers

The use of accelerometers is consolidated in the engineering community to be used in several areas and it is present in the people daily life in things like game consoles, smartphones, and tablets.

Micro Electromechanical Systems (MEMS) sensor have several applications in measuring linear acceleration or angular motion along axis as an input to control a system. MEMS accelerometer sensors often measure the movement of a mass with a position measuring interface circuit that is converted into a digital electrical signal by an analog-to-digital converter for digital processing (17).

In SHM situation, the accelerometers are in the MEMS. The MEMS are, then, embedded in the structure and can provide information about the structure by detecting low-amplitude and low-frequency vibrations that are not always viable with the conventional low-cost sensor boards (62).

There are many others sensors used in vibration-base techniques like velocity and displacement sensors, however the accelerometers are widely used for this purpose.

Graphical Inspection

The use of digital cameras to detect any kind of irregularity in the surface is also a way to monitor the structure, mainly in the surface areas. The camera itself may be static in a strategical position that allow it to provide good images to be analyzed or can be embedded in the structure itself or in an UAV that will surround it.

To automate and improve the accuracy of the damage detection, image processing techniques are employed, that being a non-conventional approach (65). In the civil engineering context, it is commonly utilized computer vision to damage detection (24) and also UAV integrated in the same local as the structures for SHM (64).

Many of the images obtained can have their not only the images improved by AI, but also the analyses can take advantage of it.

Piezoelectric Materials

When dealing with acoustic-based techniques, the use of piezoelectric materials as sensor is a great choice due to its ability to respond to stimuli, incorporation, and compatibility with construction materials. Beyond that, these materials are relatively cost-efficient and can sense vibrations in the structures they are installed (35).

Piezoelectric materials and their main property were discovered back in 1880 (16). The phenomenon is that by the application of pressure in those kinds of materials in the correct direction, it is observed the production of a potential difference and consequently an electrical charge. Examples of materials that are piezoelectric are quartz, zinc, sodium chlorate, tourmaline, calamine, topaz, tartaric acid, cane sugar, and others (12).

The application of these materials in SHM is basically to install the piezoelectric sensor in the structure intend to be monitored and through the tension or compression in it done, a sign will be sent to the central system by the potential differential. The signal indicates that something not usual is happening in the structure. Of course there are levels of the signals and each case must be evaluated in its context. In the last years the use of piezoelectric materials has been capable to identify failures, like the presence of delamination damage, as long as the piezoelectric sensors are close to the damage (45).

2.1.4 Railway Cracks

Train is one of the most used means of transportation around the world, either to transport people or groceries, therefore, there are inherent problems in the attached to it. One of the most common problems is the crack on the railway track, mainly due to the expansion and contraction caused by the heat and to constant pressure because of the wagon.

The crack in a railway is considerable problem because it may cause fatal accidents since the wagon is able to leave the railway. In this scenario, many methods are used to detect the crack or to foresee it before any misfortune happen. Karthick; Ramalingam (36) proposed a system to identify the cracks and prevent the accidents. One of its advantages is that if some crack is detected on the track, the train starts to slow and stop before it passes by there. Other method includes the use of sensor coupled in the track that allow to detect

the crack and send a signal to the command center through IoT (63).

The use of piezoelectric materials for SHM is very common, as seen in the Section 2.1.3. Loveday (43) presents a system where piezoelectric transducer are installed along the railway track. They receive an electrical wave and send it, then, a signal to the receiver, making it possible, also through Finite Element Method (FEM), to detect any inconsistency that should not be there.

There are, hence, lots of methods that can be used to detect and prevent accidents in railway tracks. Putting they together and optimize them with SHM techniques are an efficient way of improve the railway ecosystem.

2.2 Unnamed Aerial Vehicle Control

2.2.1 Usage

An UAV has several applications, going from the simplest to the most sophisticated. It can be used since for entertainment, like toys; commercially, to record big shows in arenas; surveillance, to monitor places; and also in engineering, aiding in various context to improve some processing.

Due to its portability and autonomy, it can be used to facilitate the delivery o medicines. In this sense, UAV can be used for transportation of medical goods in critical times, where other means of transportation may not be feasible. In the final of 2019, COVID-19 pandemics spread throughout the world, making it difficult to deliver patients their needed medicines (58, 47). Besides, risks are inherent to the transportation and in come countries, like the USA, UAV usage may be restricted (73). A strategical way to use them is also welcome.

In the agriculture context, in order to boost the productivity, UAV can be used to remotely sense the farming, obtaining information on the state of the fields with non-contact procedures, like nutrient evaluation and soil monitoring; or even for aerial spraying, using pesticide to prevent damages in the plantation (20).

The main reason for its adoptions is the mobility, low maintenance costs, hovering capacity, ease of deployment, etc. It is widely used for the civil infrastructure, gathering photographs faster than satellite imagery and with better quality. Combining those benefits

with AI can be a powerful tool for the future. Sivakumar; Tyj (66).

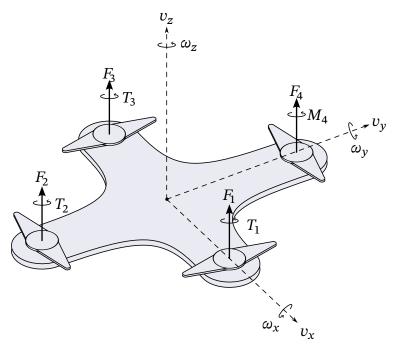
2.2.2 Motion Equation

Considering the UAV a quadcopter, as the Fig. 2.2.1 shows, it is assumed a defined coordinate system fixed in the body (Z_M). Geronel; Botez; Bueno (26), based on the work of Fossen (25), described the equation of motion for a quadcopter with a payload as being:

$$\mathbf{M}_{\eta_c}(\mathbf{\eta}_c)\ddot{\mathbf{\eta}}_c + \mathbf{C}_{\eta_c}(\mathbf{v}, \mathbf{\eta}_c)\dot{\mathbf{\eta}}_c + \mathbf{g}_{\eta_c}(\mathbf{\eta}_c) + \mathbf{K}_{\eta_c}(\mathbf{\eta}_c)\mathbf{\eta}_c = \tau_{\eta_c}(\mathbf{\eta}_c) + \mathbf{F}_d$$
 (2.2.1)

where $\mathbf{M}_{\eta_c}(\eta_c)$ is the inertial matrix; $\mathbf{C}_{\eta_c}(\boldsymbol{\nu}, \eta_c)$ is the Coriolis matrix; $\mathbf{g}_{\eta_c}(\eta_c)$ is the gravitational vector; $\mathbf{K}_{\eta_c}(\eta_c)$ is the stiffness matrix; $\boldsymbol{\tau}_{\eta_c}(\eta_c)$ is the control torque; \mathbf{F}_d is the gust vector; and $\boldsymbol{\nu}$ is the velocity generalized coordinate in the body-frame. All matrices and the development of the equations are explicit in the Geronel; Botez; Bueno (26) work.

Figure 2.2.1. Quadcopter Dynamic Scheme. F_i and T_i , (i = 1, 2, 3, 4), are the forces and the torque applied in the propeller, respectively. ω_j and v_j , (j = x, y, z), are the momentum and the velocities applied in the UAV, respectively.



Source: prepared by the author.

2.2.3 Control Algorithm

Geronel; Botez; Bueno (26) also developed a MATLAB® algorithm to control the quadrotor. It can control it in three different trajectories: rectangular, circular and linear. Given the τ as the input vector, which represents the Position Controller $U_1(t)$ and the Attitude Controller $U_2(t)$, $U_3(t)$, $U_4(t)$, it is able to give a complete overview of the quadrotor's motion.

$$\tau = \left\{ U_1 \quad U_2 \quad U_3 \quad U_4 \right\}^\mathsf{T} \tag{2.2.2}$$

The algorithm provides the state-space vector \mathbf{x}_s with the quadrotor position and angles, as their derivatives.

$$\boldsymbol{x}_{S} = \begin{bmatrix} x & y & z & \phi & \theta & \psi & \dot{x} & \dot{y} & \dot{z} & \dot{\phi} & \dot{\theta} & \dot{\psi} \end{bmatrix}$$
 (2.2.3)

2.3 Artificial Neural Networks

2.3.1 Deep Learning

The concepts of deep learning studied in this section is going to be based on the work of Goodfellow; Bengio; Courville (29), Haykin (32) and the documentation of PyTorch¹, TensorFlow² and MATLAB[®] ³.

There are several definitions of AI (78), but the computer scientist McCarthy (46) defines it as "the science and engineering of making intelligent machines, especially intelligent computer programs". He also states that "it is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable".

The big area of study is the AI and it includes several branches like fuzzy logics, robotics and machine learning. The later one, in turn, is another field with also some branches and one of them is the deep learning. However, all the three terms can be inter-

¹https://pytorch.org/docs/stable/index.html

²https://www.tensorflow.org/api_docs

³https://www.mathworks.com/help/matlab/

changeable in the major context.

The deep learning history goes back to the 1940s and it had several names over the years. It was called by *cybernetics* (1940s–1960s), *connectionism* (1980s–1990s), and from 2006 until now is known as *deep learning*. The DL models were engineered systems inspired by the biological brain and they were denominated Artificial Neural Network (ANN). One of the motivations of the neural perspective was to understand that the brain provides a proof by example that intelligent behavior is possible and try to reverse engineer the computation principals behind the brain, duplicating its functionality. Today it goes beyond the neuroscientist perspective and it is more of general principle of learning multiple levels of composition.

DL dwells in the programming sphere. The approach, however, it is not like the traditional programming scripts and models. To automate stuff, there are three main parts: (i) the input data, (ii) the rule (function) and (iii) the output data. In both types there are two of three parts available, but different ones for each other. In the traditional programming, there is the input data and the rule, for the algorithm output the data. In deep learning, there is the input data and the output data, for the algorithm provides the rule. A good analogy is cooking: in the traditional programming context, one has the ingredients and the main course to discover the recipe.

2.3.2 Neural Networks Models

A ANN is machine learning a model that simulate a biological NN to make a machine learns as the human being learns. ANN are the heart of DL and there are several models of them, each one most suitable for different kind of problems. Some of them are Multilayer Perceptron (MLP), CNN, Recurrent Neural Network (RNN), among others.

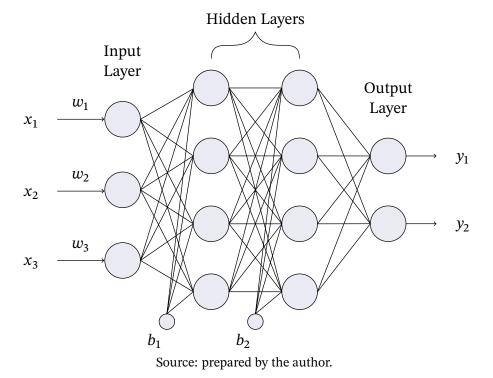
Multi-layer Perceptron

A MLP is a important class of NN. It consists of a set of sensorial units that compose the *input layer*; one or more *hidden layers*; and an *output layer*. The input signal propagates forward through the network, layer by layer. They are used to solving complex problems,

with the supervised training with the error back-propagation algorithm.

The learning by back-propagation consists of two steps through the layers of the perceptron: a forward pass (propagation) and a backward pass (back-propagation). In the forward pass, an input vector is applied to the sensorial nodes of the network and it propagates through the network, layer by layer; in this step the weights are fixed. During the backward pass, the weights are fit accordingly through a loss function (see Section 2.3.3). This error signal is propagated through the network in the opposite direction of the synaptic connections. The weights are adjusted to make that the network output gets closer of the wanted output. The Fig. 2.3.1 represents a MLP.

Figure 2.3.1. Visual Representation of a MLP. The input vector x_i is given in the input layer and i can assume any integer, just as the output data y_i . The weights w_{x_i} are specific for each input data. The bias b_i are there to prevent the data to be biased.



The three main features of the MLP are:

• Non-linear activation function. It is commonly used a smooth non-linear activation function, like a sigmoid function.

$$y_j = \frac{1}{1 + \exp(-v_j)} \tag{2.3.1}$$

where v_j is the weighted sum of all input layers with their respective weights of the j neuron; and y_i is the output of the neuron.

- Hidden layers. They allow the network to learn complex tasks, extracting progressively
 the most significantly features of the input vector.
- Connectivity. High level of connectivity, determined by the network synapses.

These features plus the ability to learn from the experience of the training that makes the MLP so powerful, however, they are also responsible for its deficiency. First, the non-linearity and the high connectivity makes hard the theorical analysis of an MLP; second, the hidden layers make it more difficult to visualize the learning processing. The learning process is harder because the search must be conducted in a much bigger space of possible functions.

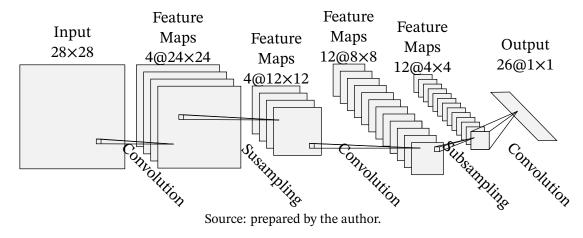
Convolutional Neural Network

A convolutional network is a MLP specifically projected to recognize two-dimensional shapes with a high-level invariance relative to translation, scaling, skew, and other forms of distortion. This task is learned in a supervised way, through these restrictions:

- Features extraction. Each neuron takes its input signals from a local receptive field in the previous layer, forcing it to extract local features.
- Features mapping. Each computational layer is composed by multiple feature maps, with each feature map in the shape of a plane within which the individual neurons are constrained to share the same weights. This provides the following benefits: (i) shift variance and (ii) reduction in the number of free parameters.
- Subsampling. Each convolutional network is followed by a computational layer that
 calculates the local averaging and performs a subsampling, reducing the resolution of
 the feature maps.

Wang et al. (77) presented an easy and more intuitive way to visualize CNNs.

Figure 2.3.2. Convolutional Neural Network. It is commonly used to process images, for instance, to recognize manuscripts, to determine objects in a picture, or to recognize patterns to make decisions based on it.



2.3.3 Loss Function

The *loss function*, also called *cost function* or *error function*, is the one used measure the error between the predicted output of an algorithm and the real target output. There are several loss functions suitable to different kind of situation. For each distributed data there is one that fits better. Many kinds of them are available and must be analyzed the most proper one to each case. The choice of what loss function should be picked will depend on not only the data and its pattern, but also the computational processing and the cost attached to it.

Regression

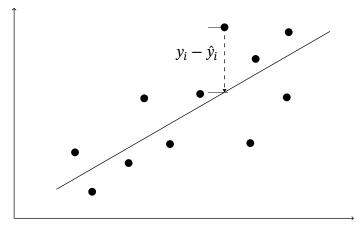
Although regression problems do not require DL to create a satisfactory model, naturally it is possible to do so. For regression problems, a common loss functions adopted is the Mean Squared Error (MSE) (13).

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$
 (2.3.2)

where *n* is the sample size; y_i is the predicted output; and \hat{y}_i is the real target.

The Fig. 2.3.3 shows a linear data and how the domain of the loss function is obtained for a linear regression.

Figure 2.3.3. Loss Function for Linear Regression. The loss function take all the distances between the predicted and the target value to verify if the model is in the right path. The lower the distance, the better the model. The *y*-axis represents the output data and the *x*-axis represents the input data.



Classification

For classification problems, a common loss function adopted is the cross-entropy. It measures the "distance" between the probability distribution and the true probability, being ideal for this kind of problem. For multi-classification, i.e., when there are more than two outputs for the model, the cross-entropy is defined as

$$H(P,Q) = -\sum_{i=1}^{n} P(x) \log Q(x)$$
 (2.3.3)

where *Q* is a discrete distribution relative *P* distribution (both discrete); and *n* is the size of the sample.

For binary classification, i.e., when there is only two outputs for the model (true or false), the cross-entropy is defined as

$$H(P,Q) = -\frac{1}{n} \sum_{i=1}^{n} x \log P(x) + (1-x) \log \left(1 - Q(x)\right)$$
 (2.3.4)

2.3.4 Optimizer

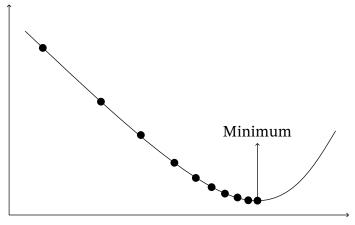
The optimizer is an algorithm that updates the model in response to the output of the loss function, that is, it aids to minimize the loss function. As the loss function minimizes,

the model is getting closer to the target values and, hence, closer to the real pattern.

Gradient Descent

The *gradient descent* is one of the main algorithm (51) that optimizes the model and many important ones are based on it, like the Stochastic Gradient Descent (SGD). The goal is to get the minimum, as the error (loss) between the predicted and the target data is null. This would mean that the model fits to the pattern of the data.

Figure 2.3.4. Gradient Descent Process. In this case, the loss function (yellow curve) can be represented in a two-axes plan. Depending on the data, it is not possible to represent graphically due to its multi dimension. Each point represents the learning step. When the gradient descent reaches the minimum of the loss function, it means that the model may be accurate. Note that the gradient descent can reach a local minimum of the function and not the global minimum necessarily. The *y*-axis represents the loss function and the *x*-axis represents the weight values.



Source: prepared by the author.

The gradient descent is a powerful algorithm that reduces the loss function, minimizing the error between the predicted value and the target value.

Since the gradient of a function gives the direction of the steepest ascent of a function and it is orthogonal to the surface at a determined point, it seems reasonable that moving in the perpendicular direction gives the maximum increase of the function (69). On the other hand, the negative of the gradient may be used to find the opposite, that is, the steepest descent of the function, or the minimum decrease. If the steps given to the direction of the negative gradient of the function are small, there is a good chance to get minimum value of the function. However, if the steps are too long, the chance to pass by the minimum value is high (52). These steps are called *learning rate* and should be chosen wisely.

This way, let x be the entry vector with the predicted data and L the loss function adopted for some deep learning model, and ϵ the learning rate, the gradient descent is:

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \varepsilon \nabla L(\mathbf{x}_t) \tag{2.3.5}$$

In determined cases, it is possible to avoid running the iterative algorithm and just go directly to the critical point by solving $\nabla L(\mathbf{x}_t) = 0$ for \mathbf{x} .

Stochastic Gradient Descent

As seen, gradient descent is a powerful tool to minimize the loss function, however, for large data, the cost of operation is very high and its use is not feasible. The main ideia of SGD is that the gradient is an expectation. Later, the data is divided in subsets, also called *mini-batch* and then the gradient is performed over them. The mini-batche size is chosen to be a realatively small numbers of examples. The data inside each subset may be considered redundant, that is why it uses one single value of the subset to compute the gradient descent. This way, the process is considerable better for computational resources.

The SGD can be written as:

$$\mathbf{x}_{t+1} = \mathbf{x}_t - \frac{\epsilon}{m} \sum_{i=1}^{m} \nabla L(\mathbf{x}_t; p^{(i)}, q^{(i)})$$
 (2.3.6)

where m is the mini-batch size; and $\nabla L(\mathbf{x}; p^{(i)}, q^{(i)})$ is the gradient of the loss function with respect to the parameter vector \mathbf{x} for the i^{th} example $(p^{(i)}, q^{(i)})$ in the mini-batch.

Yet, nowadays, with the amount of data, many techniques are still applied in SGD as creating an automatic adaptive learning rates which achieve the optimal rate of convergence (18) and the momentum technique to improve it (71).

Adam

Adam is an algorithm for first-order gradient-based optimization of stochastic objective functions, like the loss function, as seen in the Section 2.3.3. It is based on adaptive estimates of low-order moments and computationally efficient, requiring little computa-

tional memory. Adam is a strategical choice when using large data or parameters and with very noisy/sparse gradients (37).

Kingma; Ba (37) showed that the algorithm can be implemented as it follows:

```
Algorithm 1 Adam Algorithm. Good default setting are \alpha = 0.001, \beta_1 = 0.9, \beta_2 = 0.999 and \epsilon = 10^{-8}. Operations on vectors are element-wise.
```

```
Require: \alpha: stepsize
Require: \beta_1, \beta_2 \in [0,1): exponential decay rates for the moment estimates
Require: f(\theta): loss function
Require: \theta_0: initial parameter
    m_0 \leftarrow 0
    v_0 \leftarrow 0
    t \leftarrow 0
    while \theta_t not converged do
          t \leftarrow t + 1
          g_t \leftarrow \nabla_{\theta} f_t(\theta_{t-1})
          m_t \leftarrow b_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t
          v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot g_t^2
          \widehat{m}_t \leftarrow m_t/(1-\beta_1^t)
          \hat{v}_t \leftarrow v_t/(1-\beta_2^t)
          \theta_t \leftarrow \theta_{t-1} - \alpha \cdot \widehat{m}_t / (\sqrt{\widehat{v}_t + \epsilon})
    end while
            return \theta_t
```

3 METHODOLOGY

The code implementation will be pragmatical and the lines of the code will not be fully explained. The frameworks methods will not be explained either, but their documentation are reasonably comprehensive with previous programming knowledge, especially in Python and MATLAB®, and they are going to be linked whenever possible.

While the engineering goal of AI is to solve real-world problems using it as an equipment, the scientific goal is to determine which ideas explain the various sorts of intelligence (78) and the current objective is to use AI from the engineering perspective.

3.1 Softwares

3.1.1 MATLAB®

The standard in the engineering industry, MATLAB® is a powerful toolbox that...

3.1.2 TensorFlow

A framework is a group of libraries for a programming language that implements a lot of tools to facilitate some tasks. There is a lot of deep learning ones available and the most popular ones are TensorFlow (1) and PyTorch (54). While the first one was developed by Google and released in 2015 the second one was developed by Meta (Facebook), although it is now under the Linux Foundation umbrella, and released in 2016, being both opensource. Many companies, like Uber (30) and Tesla (56), use PyTorch in their AI team, while companies like Coca-Cola uses TensorFlow (72). This means that both are trustful frameworks to rely upon their built-in functions.

3.2 Neural Network for UAV Control

3.2.1 Data Generation

Since the script of Geronel; Botez; Bueno (26) provides the control torque τ as input and the state-space x_s as output vector through dynamic and control equations, the NN goal

developed is to go in the opposite direction: take x_s as the input vector and predict the τ_{η} vector as output.

The modifications in the script are minimal. The time is a discrete vector with 200 s and step 0.01, therefore the time vector has 1×20001 dimension. The "extra" value of time is the zero value.

The output vector τ has 20001×4 dimension the and the input vector \mathbf{x}_s has 20001×12 dimension.

$$\tau = \begin{bmatrix}
a_{1,1} & a_{1,2} & a_{1,3} & a_{1,4} \\
\vdots & \vdots & \vdots & \vdots \\
a_{20001,1} & a_{20001,2} & a_{20001,3} & a_{20001,4}
\end{bmatrix}$$
(3.2.1)

where the matrix column represents the control torques U_i (i = 1, 2, 3, 4).

$$\mathbf{x}_{s} = \begin{bmatrix} b_{1,1} & \cdots & b_{1,12} \\ \vdots & \ddots & \vdots \\ b_{20001,1} & \cdots & b_{20001,12} \end{bmatrix}$$
(3.2.2)

where each column represents the elements of the vector in the Eq. (2.2.3).

This way, the circular trajectory was arbitrary selected. The trajectories were generated by a loop, changing the position increasing 1/600 for each loop. It was generated 1000 different trajectories. This information is summarized in the Table 3.2.1.

Table 3.2.1. Data generation for the UAV.

Parameter	Value
Trajectory	Circular
Increase step	1/600
Time	200 s
Time step	0.01
7 11	.1 .1

Source: prepared by the author.

From there, it was generated one thousand input and output vector. Both were stored in a MATLAB® variable and exported through the .mat extension to be used with TensorFlow inside a Python environment.

3.2.2 Modeling the Neural Network with TensorFlow

The problem was considered as a regression problem, as the Eq. (3.2.3) shows. Note that the input and output are all vector.

$$f(\mathbf{p}_1(t), \dots, \mathbf{p}_{12}(t)) = \langle \mathbf{u}_1(t), \mathbf{u}_2(t), \mathbf{u}_3(t), \mathbf{u}_4(t) \rangle$$
(3.2.3)

In order to obtain a good model without consuming much computational processing, the model was created using the parameters showed in the Table 3.2.2.

Table 3.2.2. Modeling parameters.

Parameter	Value
Train sample	800
Test sample	200
Hidden layers	3
ANN per hidden layer	30
Loss function	MSE
Activation functions	Linear & ReLU
Optimizer	Adam
Optimizer learning rate	0.01
Epochs	60

Source: prepared by the author.

4 RESULTS AND DISCUSSION

This chapter shows the results obtained with the NN modeling. For both cases (SHM and UAV) the first approach is the model itself, showing the metrics and evaluating them. The second one is a comparison from the true label and the predict label for a random sample. Finally, a discussion is made based on the obtained results.

4.1 Case Study 1: Unnamed Aerial Vehicle

4.1.1 First Model

First Model Summary

After the NN training, it was tested using the 200 samples, as the Table 3.2.2. The metrics to evaluate the second model are shown in the Table 4.1.1 and in the Fig. 4.1.1.

Table 4.1.1. Model summary

Parameter	Value
MSE	0.00085
MAE	0.00746

Source: prepared by the author.

Comparison of the First Model with the Script

The Fig. 4.1.2 shows the comparison of the control torque from the script with the NN created model for the same x_s .

From the model statistics, the loss function for the test sample gave the result of 0.00085, which is an acceptable value for its purpose. Although the Fig. 4.1.2 looks like to show some discrepancy for $U_2(t)$ and $U_3(t)$, they do not mean the model did not predict precisely the control torque. After the first 10 seconds, which is the time that the UAV is leaving the ground, the model is able to describe the control torque very well.

The major error, i.e., in the beginning of the motion may be caused by the interference of the *z*-axis trajectory. The discrepancy, actually, represents very little in the major context,

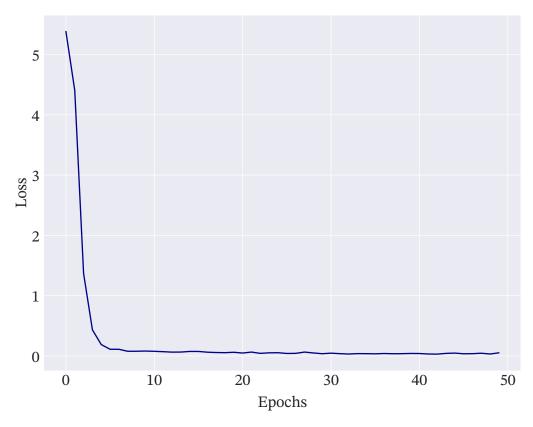


Figure 4.1.1. Loss function to the first model.

since the image scale may distort the real values. That said, other possible reason for the error in the model is the quantity of samples to make the training of the neural network. A thousand trajectories are not a good quantity for the model to make a good prediction. To have an accurate model, it should have at least one hundred thousand trajectories, but due to the processing limitation, it was not possible.

Even though the model curve did not overlap the curve from the script, it gave the same pattern.

4.1.2 Second Model

The second model has the same parameters of the first model in terms of the NN. The only difference between the two models are the input and the output data. While in the first one both the input and output data were raw, the second one the data was normalized.

The metrics to evaluate the second model are shown in the Table 4.1.2 and in

the Fig. 4.1.4. Since the data is normalized, it is notable that the trained model could

Table 4.1.2. Normalized model summary

Parameter	Value
MSE	0.00001
MAE	0.00025

predict better when comparing to the previous model. The data processing before passing to the training made the model perform at its best. This happens because all the data is in a range from negative one to positive one, while the first model this range was very high, making it difficult to predict a

4.2 Case Study 2: Structural Health Monitoring

Figure 4.1.2. Comparing the first model with the script. The continuous curve is the control torque from the script, while dashed curve is the output from the NN model.

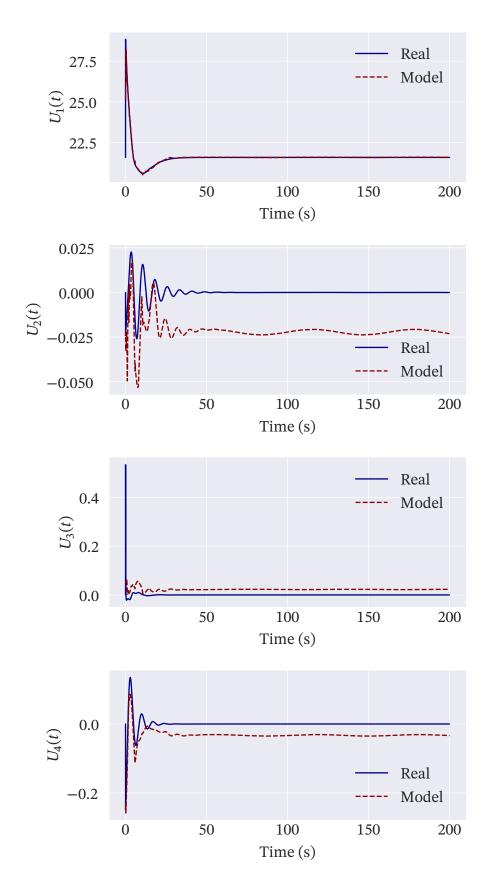
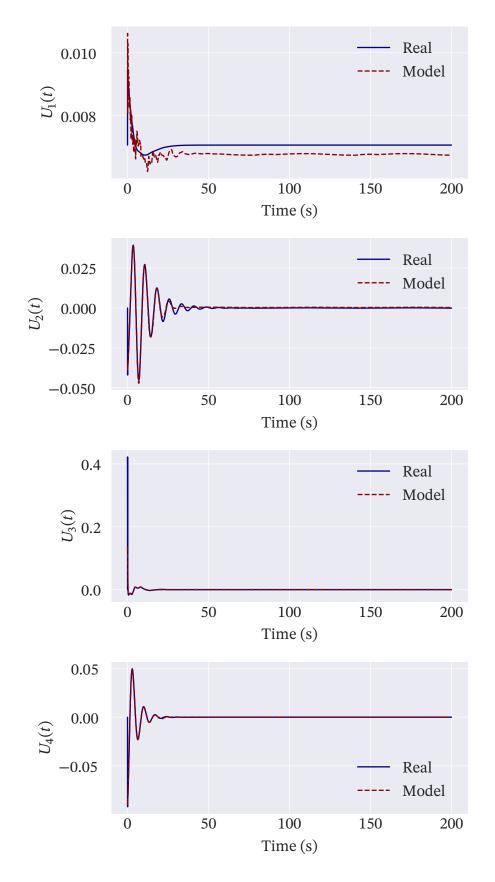


Figure 4.1.3. Comparing the second model with the script. The continuous curve is the control torque from the script, while dashed curve is the output from the NN model.



30

40

50

Figure 4.1.4. Loss function to the second model.

 $\times 10^{-3}$

1.6

1.4

1.2

S 1.0

0.8

0.6

0.4

0

10

Source: prepared by the author.

Epochs

20

5 CONCLUSION

REFERENCES

- 1 ABADI, Martin et al. TensorFlow: A System for Large-Scale Machine Learning. *12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16)*, p. 265–283, 2016.
- 2 AHIRWAR, S. et al. Application of Drone in Agriculture. *International Journal of Current Microbiology and Applied Sciences*, v. 8, n. 01, p. 2500–2505, Jan. 2019. ISSN 23197692, 23197706. DOI: 10.20546/ijcmas.2019.801.264. Visited on: 4 Apr. 2023.
- 3 ASSILIAN, Sedrak. *Artificial Intelligence in the Controle of Real Dynamic Systems*. 1974. PhD thesis – Queen Mary University of London.
- 4 AURÉLIEN, Géron. *Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow.* O'Reilly Media, Inc., 2022.
- 5 AVCI, Onur et al. Structural Damage Detection in Real Time: Implementation of 1D Convolutional Neural Networks for SHM Applications. In: NIEZRECKI, Christopher (Ed.). Structural Health Monitoring & Damage Detection, Volume 7. Cham: Springer International Publishing, 2017. P. 49–54. ISBN 978-3-319-54108-2 978-3-319-54109-9. DOI: 10.1007/978-3-319-54109-9_6. Visited on: 6 Apr. 2023.
- 6 AZIMI, Mohsen; ESLAMLOU, Armin; PEKCAN, Gokhan. Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review. *Sensors*, v. 20, n. 10, p. 2778, May 2020. ISSN 1424-8220. DOI: 10.3390/s20102778. Visited on: 4 Apr. 2023.
- 7 BAIDOO-ANU, David; OWUSU ANSAH, Leticia. Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. *SSRN Electronic Journal*, 2023. ISSN 1556-5068. DOI: 10.2139/ssrn.4337484. Visited on: 4 Apr. 2023.
- 8 BAJI, Toru. Evolution of the GPU Device Widely Used in AI and Massive Parallel Processing. In: 2018 IEEE 2nd Electron Devices Technology and Manufacturing

- Conference (EDTM). Kobe: IEEE, Mar. 2018. P. 7–9. ISBN 978-1-5386-3712-8. DOI: 10.1109/EDTM.2018.8421507. Visited on: 4 Apr. 2023.
- 9 BALAGEAS, Daniel; FRITZEN, Claus-Peter; GÜEMES, Alfredo. *Structural Health Monitoring*. John Wiley & Sons, 2010. v. 90.
- BISWAS, Som S. Potential Use of Chat GPT in Global Warming. *Annals of Biomedical Engineering*, Mar. 2023. ISSN 0090-6964, 1573-9686. DOI: 10.1007/s10439-023-03171-8. Visited on: 4 Apr. 2023.
- BISWAS, Som S. Role of Chat GPT in Public Health. *Annals of Biomedical Engineering*, Mar. 2023. ISSN 0090-6964, 1573-9686. DOI: 10.1007/s10439-023-03172-7. Visited on: 4 Apr. 2023.
- BROWN, C. et al. Piezoelectric Materials, A Review of Progress. *IRE Transactions on Component Parts*, v. 9, n. 4, p. 193–211, Dec. 1962. ISSN 0096-2422. DOI: 10.1109/TCP.1962.1136768. Visited on: 7 Apr. 2023.
- 13 BUSSAB, Wilton de O; MORETTIN, Pedro A. Estatística Básica. Saraiva Uni, 2017.
- 14 CHAN-OLMSTED, Sylvia M. A Review of Artificial Intelligence Adoptions in the Media Industry. *International Journal on Media Management*, Routledge, v. 21, n. 3-4, p. 193–215, Oct. 2019. ISSN 1424-1277. DOI: 10.1080/14241277.2019.1695619.
- COHEN-ALMAGOR, Raphael. Internet History: *International Journal of Technoethics*,
 v. 2, n. 2, p. 45–64, Apr. 2011. ISSN 1947-3451, 1947-346X. DOI: 10.4018/jte.2011040104.
 Visited on: 4 Apr. 2023.
- 16 CURIE, Jacques; CURIE, Pierre. Développement par compression de l'électricité polaire dans les cristaux hémièdres à faces inclinées. *Bulletin de la Société minéralogique de France*, v. 3, n. 4, p. 90–93, 1880. ISSN 0150-9640. DOI: 10.3406/bulmi.1880.1564. Visited on: 7 Apr. 2023.
- 17 DADAFSHAR, Majid. Accelerometer and Gyroscopes Sensors: Operation, Sensing, and Applications. *Maxim Integrated [online]*, 2014.
- 18 DARKEN, Christian; MOODY, John E. Towards Faster Stochastic Gradient Search. v. 4, 1991.

- 19 DAVENPORT, Thomas; KALAKOTA, Ravi. The Potential for Artificial Intelligence in Healthcare. *Future Healthcare Journal*, v. 6, n. 2, p. 94–98, June 2019. ISSN 2514-6645, 2514-6653. DOI: 10.7861/futurehosp.6-2-94. Visited on: 5 Apr. 2023.
- 20 DEL CERRO, Jaime et al. Unmanned Aerial Vehicles in Agriculture: A Survey. Agronomy, v. 11, n. 2, p. 203, Jan. 2021. ISSN 2073-4395. DOI: 10.3390/agronomy11020203. Visited on: 19 Apr. 2023.
- DUAN, Yanqing; EDWARDS, John S.; DWIVEDI, Yogesh K. Artificial Intelligence for Decision Making in the Era of Big Data Evolution, Challenges and Research Agenda. International Journal of Information Management, v. 48, p. 63–71, Oct. 2019. ISSN 02684012. DOI: 10.1016/j.ijinfomgt.2019.01.021. Visited on: 4 Apr. 2023.
- FARRAR, Charles R; WORDEN, Keith. An Introduction to Structural Health Monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, v. 365, n. 1851, p. 303–315, Feb. 2007. ISSN 1364-503X, 1471-2962. DOI: 10.1098/rsta.2006.1928. Visited on: 6 Apr. 2023.
- 23 FARRAR, Charles R; WORDEN, Keith. *Structural Health Monitoring: A Machine Learning Perspective*. John Wiley & Sons, 2012.
- FENG, Dongming; FENG, Maria Q. Computer Vision for SHM of Civil Infrastructure: From Dynamic Response Measurement to Damage Detection A Review. *Engineering Structures*, v. 156, p. 105–117, Feb. 2018. ISSN 01410296. DOI: 10.1016/j.engstruct.2017.11.018. Visited on: 7 Apr. 2023.
- 25 FOSSEN, Thor I. *Guidance and Control of Ocean Vehicles*. Chichester; New York: Wiley, 1994. ISBN 978-0-471-94113-2.
- GERONEL, R. S.; BOTEZ, R. M.; BUENO, D. D. Dynamic Responses Due to the Dryden Gust of an Autonomous Quadrotor UAV Carrying a Payload. *The Aeronautical Journal*, v. 127, n. 1307, p. 116–138, Jan. 2023. ISSN 0001-9240, 2059-6464. DOI: 10.1017/aer.2022.35. Visited on: 4 Apr. 2023.

- 27 GHATREHSAMANI, Shirin et al. Artificial Intelligence Tools and Techniques to Combat Herbicide Resistant Weeds—A Review. Sustainability, v. 15, n. 3, p. 1843, Jan. 2023. ISSN 2071-1050. DOI: 10.3390/su15031843. Visited on: 5 Apr. 2023.
- 28 GODA, K.; KITSUREGAWA, M. The History of Storage Systems. *Proceedings of the IEEE*, v. 100, Special Centennial Issue, p. 1433–1440, May 2012. ISSN 0018-9219, 1558-2256. DOI: 10.1109/JPROC.2012.2189787. Visited on: 4 Apr. 2023.
- 29 GOODFELLOW, Ian; BENGIO, Yoshua; COURVILLE, Aaron. *Deep Learning*. MIT Press, 2016.
- 30 GOODMAN. *Uber AI Labs Open Sources Pyro, a Deep Probabilistic Programming Language*. Nov. 2017. https://www.uber.com/en-GR/blog/pyro/. Visited on: 3 May 2023.
- GUO, Kai et al. Artificial Intelligence and Machine Learning in Design of Mechanical Materials. *Materials Horizons*, v. 8, n. 4, p. 1153–1172, 2021. ISSN 2051-6347, 2051-6355. DOI: 10.1039/D0MH01451F. Visited on: 4 Apr. 2023.
- 32 HAYKIN, Simon S. *Neural Networks: A Comprehensive Foundation*. 2nd ed. Upper Saddle River, N.J: Prentice Hall, 1999. ISBN 978-0-13-273350-2.
- 33 HUBÁČEK, Ondřej; ŠOUREK, Gustav; ŽELEZNÝ, Filip. Exploiting Sports-Betting Market Using Machine Learning. *International Journal of Forecasting*, v. 35, n. 2, p. 783–796, Apr. 2019. ISSN 01692070. DOI: 10.1016/j.ijforecast.2019.01.001. Visited on: 4 Apr. 2023.
- JEBLE, Shirish; KUMARI, Sneha; PATIL, Yogesh. Role of Big Data in Decision Making.
 Operations and Supply Chain Management: An International Journal, p. 36–44, Jan.
 2018. ISSN 2579-9363. DOI: 10.31387/oscm0300198. Visited on: 5 Apr. 2023.
- JIAO, Pengcheng et al. Piezoelectric Sensing Techniques in Structural Health Monitoring: A State-of-the-Art Review. Sensors, v. 20, n. 13, p. 3730, July 2020. ISSN 1424-8220. DOI: 10.3390/s20133730. Visited on: 7 Apr. 2023.

- 36 KARTHICK, N.; RAMALINGAM, Nagarajan. Implementation of Railway Track Crack Detection and Protection. *International Journal Of Engineering And Computer Science*, June 2017. DOI: 10.18535/ijecs/v6i5.47.
- 37 KINGMA, Diederik P.; BA, Jimmy. *Adam: A Method for Stochastic Optimization*. arXiv, Jan. 2017. arXiv: 1412.6980 [cs]. Visited on: 20 Apr. 2023.
- 38 KOLLÁR, Aladár. Betting Models Using AI: A Review on ANN, SVM, and Markov Chain.
 Mar. 2021. DOI: 10.31219/osf.io/mr2v3. Visited on: 4 Apr. 2023.
- 39 KOŚCIELNIAK, Helena; PUTO, Agnieszka. BIG DATA in Decision Making Processes of Enterprises. *Procedia Computer Science*, v. 65, p. 1052–1058, 2015. ISSN 18770509. DOI: 10.1016/j.procs.2015.09.053. Visited on: 5 Apr. 2023.
- 40 LAHMERI, Mohamed-Amine; KISHK, Mustafa A.; ALOUINI, Mohamed-Slim.
 Artificial Intelligence for UAV-Enabled Wireless Networks: A Survey. *IEEE Open Journal of the Communications Society*, v. 2, p. 1015–1040, 2021. ISSN 2644-125X. DOI: 10.1109/OJCOMS.2021.3075201. Visited on: 4 Apr. 2023.
- 41 LEE, Raymond S. T. Artificial Intelligence in Daily Life. Singapore: Springer Singapore, 2020. ISBN 9789811576942 9789811576959. DOI: 10.1007/978-981-15-7695-9. Visited on: 5 Apr. 2023.
- 42 LEINER, Barry M. et al. A Brief History of the Internet. *ACM SIGCOMM Computer Communication Review*, v. 39, n. 5, p. 22–31, Oct. 2009. ISSN 0146-4833. DOI: 10.1145/1629607.1629613. Visited on: 4 Apr. 2023.
- 43 LOVEDAY, Philip W. Development of Piezoelectric Transducers for a Railway Integrity Monitoring System. In: LIU, S.-C. (Ed.). *SPIE's 7th Annual International Symposium on Smart Structures and Materials*. Newport Beach, CA, Apr. 2000. P. 330–338. DOI: 10.1117/12.383154. Visited on: 8 Apr. 2023.
- 44 LUND, Brady D.; WANG, Ting. Chatting about ChatGPT: How May AI and GPT Impact Academia and Libraries? *Library Hi Tech News*, Feb. 2023. ISSN 0741-9058, 0741-9058. DOI: 10.1108/LHTN-01-2023-0009. Visited on: 4 Apr. 2023.

- 45 MAIO, Carlos Eduardo Bassi. Técnicas para monitoramento de integridade estrutural usando sensores e atuadores piezoelétricos. Mar. 2011. Mestrado em Dinâmica das Máquinas e Sistemas Universidade de São Paulo, São Carlos. DOI: 10.11606/D.18.2011.tde-12052011-213014. Visited on: 7 Apr. 2023.
- 46 MCCARTHY, John. What Is Artificial Intelligence? Stanford University, 2007.
- 47 MCPHILLIPS, Deidre. Home Delivery of Medications Can Help Improve Access, Especially When Time Is Tight. *CNN Health*, Dec. 2022. Visited on: 19 Apr. 2023.
- 48 MHLANGA, David. Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion. *International Journal of Financial Studies*, v. 8, n. 3, p. 45, July 2020. ISSN 2227-7072. DOI: 10.3390/ijfs8030045. Visited on: 5 Apr. 2023.
- 49 MILANA, Carlo; ASHTA, Arvind. Artificial Intelligence Techniques in Finance and Financial Markets: A Survey of the Literature. *Strategic Change*, v. 30, n. 3, p. 189–209, May 2021. ISSN 1086-1718, 1099-1697. DOI: 10.1002/jsc.2403. Visited on: 4 Apr. 2023.
- MUTHUKRISHNAN, Nikesh et al. Brief History of Artificial Intelligence.

 Neuroimaging Clinics of North America, v. 30, n. 4, p. 393–399, Nov. 2020. ISSN 10525149. DOI: 10.1016/j.nic.2020.07.004. Visited on: 4 Apr. 2023.
- 51 NESTEROV, IU E. *Introductory Lectures on Convex Optimization: A Basic Course.*Boston: Kluwer Academic Publishers, 2004. (Applied Optimization, v. 87). ISBN 978-1-4020-7553-7.
- 52 NIELSEN, Michael. *Neural Networks and Deep Learning*. Determination press San Francisco, CA, USA, 2015. v. 25.
- PANNU, Avneet. Artificial Intelligence and Its Application in Different Areas. v. 4,n. 10, 2015.
- PASZKE, Adam et al. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In: ADVANCES in Neural Information Processing Systems. Curran Associates, Inc., 2019. v. 32. Visited on: 3 May 2023.

- 55 POOLA, Indrasen. How Artificial Intelligence in Impacting Real Life Everyday.
 International Journal for Advance Research and Development, IJARnD, v. 2, n. 10, p. 96–100, 2017.
- 56 PYTORCH. PyTorch at Tesla Andrej Karpathy, Tesla. Nov. 2019. Visited on: 3 May 2023.
- 57 RABUNAL, Juan Ramon; DORADO, Julian (Eds.). *Artificial Neural Networks in Real-Life Applications*. Hershey PA: Idea Group Pub, 2006. ISBN 978-1-59140-902-1 978-1-59140-903-8 978-1-59140-904-5.
- RAMAKRISHNAN, Manasvini et al. Impact of COVID-19 Pandemic on Medicine Supply Chain for Patients with Chronic Diseases: Experiences of the Community Pharmacists. *Clinical Epidemiology and Global Health*, v. 20, p. 101243, Mar. 2023. ISSN 22133984. DOI: 10.1016/j.cegh.2023.101243. Visited on: 19 Apr. 2023.
- 59 RASCHKA, Sebastian. *Python Machine Learning*. Packt Publishing Ltd, 2015.
- 60 RASCHKA, Sebastian et al. Machine Learning with PyTorch and Scikit-Learn: Develop Machine Learning and Deep Learning Models with Python. Packt Publishing Ltd, 2022.
- RUIZ-REAL, José Luis et al. Artificial Intelligence in Business and Economics
 Research: Trends and Future. *Journal of Business Economics and Management*, v. 22,
 n. 1, p. 98–117, Oct. 2020. ISSN 1611-1699, 2029-4433. DOI: 10.3846/jbem.2020.13641.
 Visited on: 5 Apr. 2023.
- 62 SABATO, Alessandro; NIEZRECKI, Christopher; FORTINO, Giancarlo. Wireless MEMS-Based Accelerometer Sensor Boards for Structural Vibration Monitoring: A Review. *IEEE Sensors Journal*, v. 17, n. 2, p. 226–235, Jan. 2017. ISSN 1530-437X, 1558-1748, 2379-9153. DOI: 10.1109/JSEN.2016.2630008. Visited on: 7 Apr. 2023.
- 63 SAKENA BENAZER, S. et al. Efficient Model for IoT Based Railway Crack Detection System. *Materials Today: Proceedings*, v. 45, p. 2789–2792, 2021. ISSN 22147853. DOI: 10.1016/j.matpr.2020.11.743. Visited on: 8 Apr. 2023.
- 64 SANKARASRINIVASAN, S. et al. Health Monitoring of Civil Structures with Integrated UAV and Image Processing System. *Procedia Computer Science*, v. 54, p. 508–515, 2015. ISSN 18770509. DOI: 10.1016/j.procs.2015.06.058. Visited on: 7 Apr. 2023.

- 65 SHARMA, Arabinda; MEHTA, Neeraj. Structural Health Monitoring Using Image Processing Techniques-A Review, Aug. 2016.
- 66 SIVAKUMAR, Mithra; TYJ, Naga Malleswari. A Literature Survey of Unmanned Aerial Vehicle Usage for Civil Applications. *Journal of Aerospace Technology and Management*, v. 13, e4021, 2021. ISSN 2175-9146. DOI: 10.1590/jatm.v13.1233. Visited on: 19 Apr. 2023.
- 67 SMARSLY, Kay; LEHNER, Karlheinz; HARTMANN, Dietrich. Structural Health Monitoring Based on Artificial Intelligence Techniques. In: COMPUTING in Civil Engineering (2007). 2007. P. 111–118.
- 68 SOHN, Hoon et al. A Review of Structural Health Monitoring Literature 1996 200. Los Alamos National Laboratory, USA, Citeseer, v. 1, p. 16, 2003.
- 69 STEWART, James. *Calculus*. EIghth edition. Boston, MA, USA: Cengage Learning, 2016. ISBN 978-1-285-74062-1 978-1-305-27176-0.
- 70 SUN, Limin et al. Review of Bridge Structural Health Monitoring Aided by Big Data and Artificial Intelligence: From Condition Assessment to Damage Detection. *Journal of Structural Engineering*, v. 146, 2020.
- 71 SUTSKEVER, Ilya et al. On the Importance of Initialization and Momentum in Deep Learning, p. 1139–1147, 2013.
- 72 TENSORFLOW. The Coca-Cola Company Using TensorFlow for Digital Marketing Campaigns (TensorFlow Meets). Aug. 2018. Visited on: 26 May 2023.
- THIELS, Cornelius A. et al. Use of Unmanned Aerial Vehicles for Medical Product
 Transport. *Air Medical Journal*, v. 34, n. 2, p. 104–108, Mar. 2015. ISSN 1067991X. DOI: 10.1016/j.amj.2014.10.011. Visited on: 19 Apr. 2023.
- TZOUNIS, Antonis et al. Internet of Things in Agriculture, Recent Advances and Future Challenges. *Biosystems Engineering*, v. 164, p. 31–48, Dec. 2017. ISSN 15375110. DOI: 10.1016/j.biosystemseng.2017.09.007. Visited on: 4 Apr. 2023.

- VERDOUW, C.; WOLFERT, S.; TEKINERDOGAN, B. Internet of Things in Agriculture.

 CABI Reviews, v. 2016, p. 1–12, Jan. 2016. ISSN 1749-8848. DOI:

 10.1079/PAVSNNR201611035. Visited on: 4 Apr. 2023.
- VERMA, Sanjeev et al. Artificial Intelligence in Marketing: Systematic Review and Future Research Direction. *International Journal of Information Management Data Insights*, v. 1, n. 1, p. 100002, Apr. 2021. ISSN 26670968. DOI: 10.1016/j.jjimei.2020.100002. Visited on: 5 Apr. 2023.
- WANG, Zijie J. et al. CNN Explainer: Learning Convolutional Neural Networks with Interactive Visualization. *IEEE Transactions on Visualization and Computer Graphics*,
 v. 27, n. 2, p. 1396–1406, Feb. 2021. ISSN 1077-2626, 1941-0506, 2160-9306. DOI: 10.1109/TVCG.2020.3030418. arXiv: 2004.15004 [cs]. Visited on: 24 May 2023.
- WINSTON, Patrick Henry. *Artificial Intelligence*. 3rd ed. Reading, Mass: Addison-Wesley Pub. Co, 1992. ISBN 978-0-201-53377-4.
- YE, X.W.; JIN, T.; YUN, C.B. A Review on Deep Learning-Based Structural Health Monitoring of Civil Infrastructures. *Smart Structures and Systems*, v. 24, n. 5, p. 567–585, Nov. 2019. DOI: 10.12989/SSS.2019.24.5.567. Visited on: 4 Apr. 2023.
- YU, Kun-Hsing; BEAM, Andrew L.; KOHANE, Isaac S. Artificial Intelligence in Healthcare. *Nature Biomedical Engineering*, v. 2, n. 10, p. 719–731, Oct. 2018. ISSN 2157-846X. DOI: 10.1038/s41551-018-0305-z. Visited on: 5 Apr. 2023.