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Complexity engineering: how subjective issues become objective

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Abstract

This study details the substantial technological progress experienced in the last few decades, its impact on engineering, how machine learning and data science can contribute to solving human problems. The objective here is to establish the principles of "Complexity Engineering" based on the works of Edgar Morin. Thus, initially, a history of the events, discoveries, and disruptive inventions that marked Engineering in recent centuries is made, and conceptual considerations and practical applications of Complexity Engineering in different areas of knowledge are shown. The idea is to provide a historical perspective of engineering development that started before the advent of scientific methodological contributions and is based on accurate observation of natural behaviors. Since Galileo and Newton's objective vision, scientific progress strongly influenced engineering progress, leading to the creation of unthinkable wonders, allowing spatial trips, and mainly, providing a more comfortable daily life. However, two important new issues have emerged: ways to relate this progress with life on Earth, and techniques to use the big data available to improve methodological engineering attitude. In this study, these questions are discussed, and we have shown that objectively obtained big data can be used to address subjective human problems, creating a new discipline called complexity engineering.

Keywords: complex system; complexity measures; machine learning; information entropy

1 Introduction

Engineering as a human endeavor has a long history marked by disruptive events, discoveries and inventions that changed the ways of understanding the world and the universe and acting on them. The virtuous cycle between advances in Engineering and Science was gradually consolidated, being significantly influenced by paradigms that shaped the worldviews of engineers and scientists at each time.

Since prehistoric times, Engineering has been a part of human life and has led to the development of weapons for hunting and tools to convert hunted animals into food[1]. Shelters were created to protect against bad weather, and fire was discovered, allowing food preparation and furnishing necessary heat to guarantee living conditions [2, 3][2]. The 1^{st} Agricultural Revolution, which marks the change in the way of life from hunter-gatherer to that of sedentary farmer, required our ancestors to develop new tools and new ways of occupying geographic space suitable for this new transition in the history of humanity [5].

In ancient great civilizations, Engineering played a fundamental role in the consolidation and expansion of their empires. In the Egyptian civilization, the building industry developed with remarkable constructions and the invention of cement, combining polishing materials with gypsum and water. The

[1]This fact is brilliantly illustrated in the classic scene from Stanley Kubrick's film '2001: A space odyssey' [1], based on the book of the same name by Arthur C. Clarke and set to the song 'Also Sprach Zarathustra', by Richard Strauss (in turn inspired by the book by Friedrich Nietzsche of the same title). The scene begins with an ancestral hominid discovering that the bone of an animal can be used as a weapon for hunting and ends with a scene transition of this bone thrown upwards and its 'replacement' by a ship in space, summarizing in a few minutes how the transformation of elements and processes of nature into tools is a striking feature of human history.

[2]Another classic film shows the importance of our ancestors' mastery of fire: 'Quest of Fire', by Jean-Jacques Annaud [4].

Greeks improved building techniques by combining aesthetics with construction abilities and used precision cutting techniques to build columns and large structures that have persisted from VII B.C. until now [6, 7].

According to the best engineering patterns, all such works were carried out, and monuments were built without the knowledge of physics laws, resulting from accurate natural observation and meticulous techniques [6]. Following this heritage, the Romans invented concrete and developed advanced building technologies for large structures. In addition, urban concepts began to appear, with water distribution and roads playing an important role in improving human life [6, 8].

The XVI century can be viewed as a time corresponding to the transition from empirical engineering to a scientific way of thinking about problems using formal mathematical ideas and initial natural laws. Simple machines, such as pulleys, gears, and levers, were used for power transmission and force multiplication [8]. Inspired by a vision brought by the Scientific Revolution that was taking place during this period, Engineering adopted the mechanistic-deterministic paradigm as its guide and the mastery of nature as its objective.

Such a paradigm, focused on the isolated understanding of each part of a system and the conception that the whole is simply the sum of these parts [9], has often caused engineers and scientists to interpret challenges as if they were 'tame' or 'benign' and not as 'wicked' problems [10].

However, problems that humanity currently faces are increasingly complex and interconnected, requiring a new approach to finding solutions to them. Nowadays, exploring a new way of thinking, called "Complexity Paradigm", has proven to be a suitable worldview for this purpose. Complex ideas are pervading science in the XXI century, as evident from the 2021 Physics Nobel Prize [11], which recognized a multidisciplinary methodology of pursuing science that must be extended to technological issues, legitimizing the concept of "Complexity Engineering" [12, 13].

The objective of this study is to establish the principles of "Complexity Engineering" based on the works of Edgar Morin [14, 15]. Thus, initially, a history of the events, discoveries, and disruptive inventions that marked Engineering in recent centuries is made (Section 2), and then, in the next sections, conceptual considerations and practical applications of Complexity Engineering in different areas of knowledge are shown.

In Section 3, these principles are described in connection with a case study of design and building processes, considering that they are composed of open systems [16], have nonlinearities and noise [17], and lead to the emergence of unexpected and self-organized behavior [18]. In turn, Section 4 focuses on one of the pillars of Artificial Intelligence, highlighting how the theoretical-conceptual bases and advances in Computer Engineering are applied to Machine Learning.

In sequence, Section 5 describes ways to measure complexity using concepts derived from Claude E. Shannon's information theory [19], followed by Section 6, which explains a method to formulate an engineering problem in a complex manner and presents two examples, one from behavior science and the other from environmental science, showing the diversity of possible applications of complex engineering tools to convert human issues into objective variables.

2 Engineering and its fruitful history in partnership with Sciences and Mathematics

As previously pointed out, the XVI century marks a change from empirical engineering to one strongly based on Science and Mathematics.

In the XVII and XVIII centuries, hegemonic nations created military academies, where building techniques were taught and developed, allowing skilled armies to build ships, roads, bridges, and weapons essential for dominating new unknown territories [8]. At that time, engineering knowledge built and modified nature, allowing comfort and quality of life for human beings from a naturalist perspective. Engineering was guided by rational interpretations, and people started to use Galileo's scientific method to systematize the development of engineering knowledge as a discipline based on mathematics and emerging physics [20]. French scientists such as Poisson, Navier, Coriolis, Poncelet, and Monge defined a technological approach based on scientific knowledge, resulting in the creation of École Polytechnique in Paris in 1774, where research and engineering activities were initiated with a theoretical systematization [20].

Additionally, in 1794 in Paris, École de Mines started to teach and develop technological disciplines to explore mineral resources in a scientific manner. Combined with the simultaneous popularity of positivism, this turned engineering into a respected profession, and many new schools were created worldwide: Praga (1806), Vienna (1815), Karlsruhe (1825), Munich (1827), MIT (1865), Carnegie Mellon (1905), and Caltech (1919) [20].

As a consequence of the strong industrial development based on thermal machines, such a technological environment improved the automation of production processes and transformed the means of mass transportation. In addition, the automotive industry was born, and individual mobility began to change urban life all over the world [21].

Simultaneously, the phenomenon of electromagnetism, discovered by Michael Faraday (1791-1867), provided the possibility of producing electrical currents by magnetic flux variations. Owing to the work of Nikola Tesla (1856-1943), electromagnetism was used to build electrical machines, allowing massive generation and transmission of energy over geographically distributed regions [22]. Combined with the automotive industry, electrical power distribution facilities modified the means of production and transformed daily human life in urban and rural areas [23]. In 1899, Guglielmo Marconi (1874-1937) conducted the first wireless communication through the English Channel [24]. This historic achievement was based on the ideas of Faraday and Tesla, the experiments of Hertz (Henrich Hertz 1857-1894), and involved the remarkably general Maxwell equations (James Clerk Maxwell:1831-1879).

As a consequence of the new facilities of energy distribution and communication, the 20th century experienced remarkable development in material science, which was the building block for big infrastructure projects, industrial manufacturing, all modes of transportation, more productive crops, and health care, ensuring a more comfortable daily life [25]. At the same time, the Manhattan Project, headed by Julius Robert Oppenheimer in the middle of that same century, showed how Engineering and Science, combined with computation technology development [21, 24], can come together to design and execute a large project, and demonstrated that both are not separated from society and that they need to be based on ethical principles [26]. Thus, although this project managed to promote the 'art of directing the great sources of power in nature for the use and convenience of man' (a reference to the objective of Civil Engineering present in the Royal Charter of the Institute of Civil Engineering of 1828 [27], its consequences for humanity itself was strongly contested, including by Oppenheimer himself.

This newly developed scientific and technological environment, as well as the dilemmas brought by it, generated feedback on ideas, with the entire knowledge behavior modeled as a general feedback system [7, 28, 29]. A new scientific paradigm emerged from the action of overly many thinkers around the world, nowadays called "Complexity", that combined with data science has been producing an important methodological revolution [30].

3 Complexity engineering principles

The current concept of engineering problems is based on the disjunction principle, i.e., the entire problem is viewed as a system composed of interacting parts that are studied independently, with the interactions defined by the technical specifications of each part [31].

Adapting the advances to system theory proposed by Edgar Morin [14], the engineering design process can be improved by considering the internal interactions of the system more accurately, considering the inherent nonlinearities and stochastic behavior related to the parts [30]. Such thinking allows the prediction of cascade bifurcations owing to long-term parameter variations, avoiding spurious oscillations and chaotic behaviors [18] and establishing precise models for perturbations and noise [32].

Extending this approach to the interactions between a system and the environment permits modeling of possible mutual effects of physical, chemical, biological, economic, and social phenomena [11–13, 33], approaching engineering problems to the concept of wicked problem, which emerged to characterize problems related to social policies [10].

As mentioned earlier, complexity theory can be applied to engineering problems and considers the possible emergence of unexpected behaviors due to internal nonlinearities and randomness [35]. In addition, the system must be conceived as open, with all external constraints playing a role in the design conception [36]. Scaling laws is another fingerprint of complex systems, which would be detected by multiscale approaches [37].

It must be noted that Complexity, in this context, has a connotative meaning that differs from the usual ideas of structural complication and many equation models, i.e., it is related to the way of seeing an object as open, nonlinear, stochastic and self-organized [38].

An elevated road, which is a highly complex engineering construction, can be used to illustrate these concepts. The design process begins with the necessity of connecting two places separated by a geographic factor that prevents or hinders the traffic of vehicles and people. In the initial phase, economic, social, environmental, and financial constraints determine the localization and maximum budget allowed to define the first specifications to initiate the design process.

Possible natural forces, permissible loads owing to traffic, and geometric factors need to be considered in calculations. Internal efforts and possible atmospheric variations determine the types of materials, beams, pillars, paving, and structural supports. This phase is followed by the executive project. The material and labor costs are detailed to translate ideas from the paper to the real world. Building work is demanding and constant follow-ups are needed to solve unexpected and unavoidable problems during implementation.

After the inauguration, elevated roads must be maintained, with constant measurements using position and load sensors. Such monitoring allows the prevention and correction of faults. Hence, it is well known that conceiving, designing, building, and maintaining a bridge is a complex (complicated) engineering problem.

An emblematic example of this work is shown in Figure 1, with a lateral view of the "Elevado João Goulart", built in São Paulo downtown at the end of the 1960s, which is well maintained and operational till now.

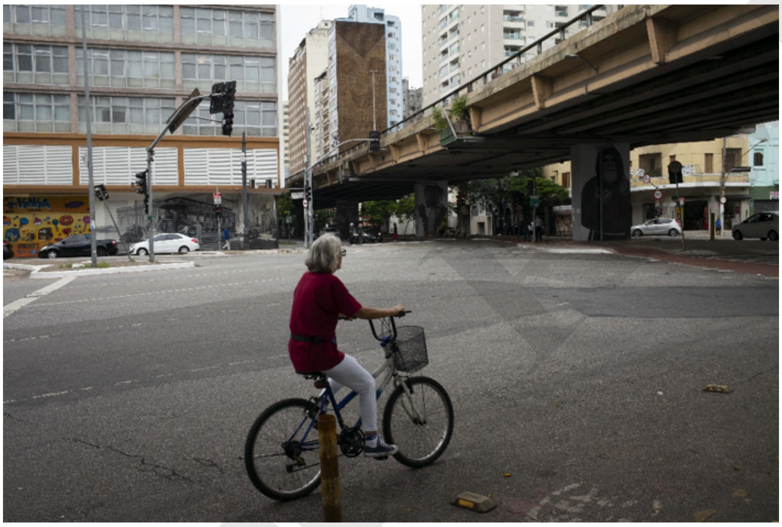

Figure 1: A lateral view of "Elevado João Goulart". (Photographed by Thales Trigo in 2022).

Considering this way of thinking, i.e., the good operational behavior of the elevated road as a robust structure to resolve traffic issues, it was built and designed as a closed system, not considering several environmental and human questions.

However, as shown in Figure 2, the elevated road was built in a populated region, due to which noise, traffic jams, and pollution degraded life in the neighborhood. Hence, the first ideas to consider the "Elevado João Goulart" as an open system were born. Some new variables related to the interactions between the "Elevado" and the environment became important to the population's health. Air quality degradation and acoustic noise can increase the prevalence of cardiorespiratory diseases and hearing loss.

As a new engineering facility is intended to improve life, these variables must be considered when a project is conceived. However, at that time, it was very difficult to consider these factors because there were not enough databases and only subjective ideas could be traced. Currently, many computational and communication algorithms and databases allow the conversion of epidemiological and environmental data into objective boundary conditions to conceive and implement a new engineering well [39].

Figure 2: "Elevado João Goulart" built in a densely populated area. (Photographed by Cristiano Mascaro in 1986).

Additionally, in the case of the "Elevado", economic and social effects appeared due to hidden stochastic and nonlinear variables [40], provoking the emergence of radical changes under the "Elevado," creating poorness niches and degrading the local commerce (Figure 3).

Figure 3: View from the region under "Elevado" (Photographed by Cristiano Mascaro in 1986).

However, self-organization [32], an important natural and human phenomenon, operates positively.

People living around the “Elevado” pressured the local administration to free the road from weekend traffic, allowing a recreational space (Figure 4). This attitude led to a decrease in pollution and improved the quality of life of the inhabitants.

Figure 4: “Elevado” free from traffic (Photographed by Thales Trigo in 2022).

Another self-organizing attitude was the conception of a low-cost open market (“feira livre”) (Figure 5), which provided food suitable for the acquisitive conditions of the neighborhood. Transformations in the “Elevado João Goulart” are part of a project to requalify the central region of São Paulo, which includes the “Belvedere Roosevelt” lookout.

Figure 5: “Feira livre” under the “Elevado João Goulart” (Photographed by Thales Trigo in 2022).

It is a remnant area of the structure designed to connect the ”Elevado” with other streets that will have rain gardens. The use of this nature-based solution demonstrates a shift from engineering solutions based exclusively on gray infrastructure to the inclusion of so-called blue and green infrastructure.

In a nutshell, by observing the “Elevado João Goulart” and its neighborhood from its conception up to now, it is possible to understand an engineering action from a complexity perspective: open, nonlinear, stochastic, and self-organizing systems. The issue of excess subjective variables can be addressed using new artificial intelligence procedures.

4 Machine learning (ML)

Previously, anonymous engineering designers and workers learned techniques based on empirical data and reality sensing to build the Egyptian pyramids, Greek monuments, and Roman urban facilities.

Likewise, in modern times, machine learning (ML) techniques have allowed the exploration of important aspects of phenomena that are not dominant in the current science stage.

The seeds of the ML revolution can be found in Alan Turing's seminal papers [41–45], published in the middle of the 20th century, which were improved by extreme electronic miniaturization and by building solid-state memories. Consequently, the main obstacles faced in Turing's time, i.e., low computational speed and magnetic memories, have been overcome by very fast processors and high-capacity memory.

During World War II, on December 8th, 1943, the first electronic digital computer (Colossus) began operating. It was built by the engineering team of Thomas Flowers at the Post Office Research Station in Dollis Hill, London [41]. As Jack Copeland [41] pointed out, Colossus contained 1,600 electronic valves, while von Neumann's IAS computer, built at the Princeton Institute of Advanced Studies in 1952, had 2,600.

However, Colossus lacked two important features: it was not able to store programs internally, and not being a general-purpose machine, as it was built for cryptanalytic tasks. In this context, on October 1st, 1945, Turing started to work at the Mathematics Division of the National Physical Laboratory (NPL) at Teddington, London [41], looking for a general-purpose computer machine as a concrete form of the Turing machine [46].

Turing's approach to building the machine was different from that of von Neumann [47]. He attempted to avoid additional hardware-privileging software, i.e., complex behavior achieved by programming instead of complex hardware. In 1947, Sir Charles Galton Darwin, the Director of NPL, worried about the slow progress in building the machine proposed by Turing, authorized him to spend a sabbatical at Cambridge to improve the theoretical basis of the whole work [42].

Facing technical and religious prejudices, the results of the sabbatical period were presented in 1948 as a report titled "Intelligent Machinery" [42] that was complemented by the seminal paper "Computer Machinery and Intelligence" [43] published in the journal "Mind", in 1950.

The Turing test (imitation game) was described by combining software principles with the concept of computable numbers [48]. Then, mathematical and technological criticisms were answered with the proposition of a robust architecture, even considering Godel´s "Incompleteness theorem" [44, 49]. These ideas were developed due to the decisive participation of Alonzo Church and led to the "Church-Turing test" [44, 45].

Turing's ideas about natural and artificial intelligence, mainly reported in references [41, 45], have been converted into real computer systems and devices. These have been supported by the development of cheap memory devices and fast processors, owing to strong electronic miniaturization at the end of the 20th and the beginning of the 21st century.

Expert systems are ML programs that can provide advice regarding specific fields of knowledge [50], such as medical diagnosis or corporate planning [42]. These systems consist of a database complemented by an inference rule and a search engine [51]. The inference rule is engineered using information obtained either from human experts, building supervised learning (SL) systems, or inferred from collected actual data, constituting unsupervised learning systems (UL) [39].

Connectionism, another ML method, considers unorganized artificial networks as the simplest model of the central nervous system. This approach is described in McCulloch and Pitts's work [52] and suggests a learning process resulting from interference with training between the connected neurons, adjusting the connection weights. McCulloch and Pitts neuron, combined with the concept of a "B-type unorganized machine" [42], inspired the modeling of cognitive systems as artificial neural networks [53], i.e., devices with self-organized learning.

Experiments with systems trained to learn language rules, such as correctly forming the past tense of irregular verbs [54], conducted in the mid-1980s, contributed to the popularization of connectionism strategies in ML development.

Currently, the two main approaches to ML and their combinations have resulted in many methods and strategies that can be adequately applied to all problems. The process of designing an ML model begins with the type of task to be performed: "classification", "regression", or "regression-classification" [39].

Classification tasks are used to define the boundaries between classes. For instance, determining whether an image showing a tumor corresponds to a malignant case [51]. In such cases, the learning mechanism can be implemented by a specialist medical doctor who observes the data and adjusts the inference strategies in an expert system or by the weights in a neural network.

This study assumes that there is a reasonable set of available training data and that the ML process is engineered based on a supervised learning mechanism. When training data are not available in advance, the criteria must be defined, and part of the working data is used to establish inference strategies or weights [50].

Regression tasks involve obtaining mathematical relations between relevant variables in a process that can be modeled by relating either objective, measurable variables, or subjective human feelings, such as fashion preferences, happiness, humor states, or any other expressible sensation. According to the problem to be modelled, adequate scales must be established to give ideas about how subjective variables can be represented by objective measures [55, 56].

Regression and classification must be used together for certain types of problems when the mathematical relationships among the problem variables must define the boundaries. Regression defines the boundaries setting the classification ranges, with learning mechanisms that function similarly to the development of biological and social life [57, 58].

In this context, machine learning algorithms such as transformer deep-learning architecture [59] have enabled sophisticated implementation of regression, classification, or regression-classification tasks. The pinnacle of such progress is represented by notable advancements in Natural Language Processing (NLP), for instance, prominently showcased by models GPT-3.5 and GPT-4 that are used to power ChatGPT [60].

5 Complexity measures

The science of complexity involves several traditional disciplines: computation, ecology, economics, management, politics, and social sciences. Although life is governed by the laws of physics, physics cannot predict life [61].

All engineering activities involve interventions in nature aimed at improving life on the planet. A good project requires a non-disjunction complexity approach, considering complexity concepts, i.e., circular causality, sensitivity to initial conditions, emergence, and unpredictability owing to an open system view [61].

Such reasoning requires consideration of variables and parameters that are essential to operate a project, even though it is difficult to associate them with quantitative figures. The classical statistical method can be used to treat time series, complemented by measures that discuss the unpredictability and self-organization of the entire system [62–64].

Some ideas about complexity measures have been developed, and these originated in computer science. Such methods attempt to quantify the extent of complication in a program as well as the memory space needed to execute computational tasks [65].

Kolmogorov's ideas about complexity measures are related to algorithms and conformal mapping [66, 67] represented by programs implemented by a universal Turing machine (UTM), which is the basis for the "Algorithmic information theory (AIT)" [46].

Considering the AIT perspective, any particular event "x" from an ensemble is treated as a variable consisting of a symbol sequence, either deterministic or random, thus leading to the following definition [46]:

- complexity K(x) is the smallest program q(x) that generates x.
- q(x) comprises a finite set of binary instructions of length |q(x)| bits.
- q(x) can be implemented using a Turing machine (TM).

Then, min|q(x)| = K(x) is called the complexity of x and can be referred to as *algorithmic information content, algorithmic complexity, algorithmic entropy*, or *Kolmogorov complexity* [46].

Another way to define complexity is to follow *"Shannon´s information theory (SIT)"* [19], according to which events x_i analogous to messages belonging to a discrete source are able to generate N different messages, each with probability pi. The mean value of the information generated by the source is expressed as

$$S = -\sum_{i=1}^{N} p_i log_2(p_i) \tag{1}$$

where, S is the "source entropy" or "informational complexity," measured in bits/symbol [40, 63, 64].

The definition in (1) assumes finite discrete sources, but due care is required to define S for continuous sources and infinite domains, as proved in [68].

Since Shannon proposed the definition of entropy in the context of SIT, there has been considerable discussion on the relation between this idea and the definition of entropy in the context of thermodynamics. This aspect is beyond the scope of this work. However, interesting and clarifying text can be found in [69, 70].

The algorithmic and information perspectives are approximately equal for sources corresponding to a large number of events, i.e., the mean value of K(x), with x belonging to source X, is approximately equal to S, calculated over the same source [71].

Considering the equivalence between the definitions of K(x) and S, in this study, only S is considered to support the several proposed definitions of complexity.

As proved in [72], the maximum value of S occurs when the events are equiprobable, i.e., $S_{max} = log_2 N$, corresponding to the maximum disorder of the event distribution. Consequently, it is possible to define the relative disorder (Δ) for a set of possible symbols, states, or variables as

$$\Delta = \frac{S}{S_{max}} \tag{2}$$

The disorder measure (Δ), expressed by (2), was the first idea of a general measure of complexity and was analogous to the manner of expressing complexity when computational tasks were evaluated [62, 73].

However, when this method of defining complexity is applied to natural and self-organized systems, for instance, in biological or ecological contexts, an important criticism emerges because, in such cases, the real complex behavior is a combination of disorder and emergent order [62, 73].

To adjust the complexity of quantitative definitions to real natural phenomena, ideas that combine disorder and order measures have been developed [74, 75]. The simplest method is to define the order measure D, which was proposed in [75] by Shiner, Davison, and Landsberg (SDL) as the complement of disorder. Consequently, the SDL complexity measure (C_{SDL}) results from the product of the disorder measure and its complement:

$$C_{SDL} = \Delta(1 - \Delta) \tag{3}$$

López–Ruiz, Mancini, and Calbet (LMC) proposed another method to measure complexity. They conceived a different approach to measure the order term (D), expressing the distance between the considered probability distribution and the uniform distribution [74]:

$$D = \sum_{i=1}^{N} (p_i - \frac{1}{N})^2 \tag{4}$$

This allowed the expression of López-Ruiz, Mancini, and Calbet (LMC) complexity (C_{LMC}):

$$C_{LMC} = D\Delta \tag{5}$$

Expressions (3) and (5) are convex functions that present maximum values when the order and disorder are equivalent. Complementarily ordered or disordered systems are zero-complexity situations compatible with intuitive reasoning regarding nature [62, 65, 73].

Furthermore, the expressions of C_{SDL} and C_{LMC} can be generalized to continuous systems [71] and quantum information contexts [76, 78]. It should be noted that C_{SDL} and C_{LMC} not measure deterministic complexity but structural complexity [37, 79].

6 Complex Engineering Approach: Examples

Many advances in Engineering derived from his classic method: breaking down of most engineering projects into many pieces. However, as shown in the example of "Elevado João Goulart", this approach ignores the processes of emergence and self-organization that occur in complex systems and the wicked problems that Engineering deals with. The construction of sustainable cities and with structures resilient to climate change is another example that these objectives cannot be achieved with a 'Lego' Engineering approach.

The former sections suggested an approach to apply complexity ideas to engineering projects, in which objective measures were complemented with subjective issues and then converted into objectives in the following manner:

- Identify processes that are inherently difficult to measure.
- Classify possible subjective impressions by attributing grades.
- Attempt to obtain larger, different real situations as classified earlier.
- Design a computational program to process the obtained large datasets.
- Design an algorithm to calculate the order, disorder, and complexity parameters.
- Discuss and present conclusions regarding the meaning of the calculated parameters.

Diverging from the tractable nature of 'tame problems' that align with conventional engineering paradigms, the domain of 'wicked problems' is characterized by the absence of a definitive solution and mandates a singular contextualized approach, presented above by the systematic framework of procedures. Hence, the discipline of complexity engineering is responsible for addressing the nuances of each situation and converting the subjective into the objective.

This discourse presents two examples in which the methodology for objective and quantitative analysis of complex situations is contextualized and applied. These examples encompass human behavior and environmental science. Nevertheless, the scope of this exposition is delimited to the presentation of these particular cases. It is imperative to emphasize that the framework of procedures to solve a 'wicked problem' is employed systematically, and there is no loss of generality.

6.1 Behavior in a psychiatry ward

As a first example of this line of reasoning, the problem related to a former psychiatric ward at the end of the 1990s in the Clinics Hospital of São Paulo University is extended, based on [56]. It shows the way subjective inpatient states can be converted into objective, observable variables processed by a back propagation neural network [39], allowing possible actions to improve the quality of human life.

This work can be considered as a pioneer work. Despite not being a traditional engineering problem, it follows the new way of doing science, without considering rigid knowledge frontiers. Nowadays, profitable studies are being developed in the same context with profitable dialogs between areas [80].

It must be noted that such wards were discontinued due to Brazilian mental health policies, and the data were only used to show the approach to analyze an apparently subjective issue by assuming it as objective.

The first step, i.e., to identify processes to be measured was proposed in Ref. [39] published in 1999. It described a psychiatric ward, surveyed the behavior of 68 inpatients over 62 days, and assigned a daily score regarding the sociability and restlessness of each individual.

Data were collected from acute patients consecutively admitted to a female psychiatric unit. The ward had a capacity of up to 30 inpatients. The mean stay period was 42.7 days, and the shortest duration in the ward was two days.

The main criteria for admission to the inpatient unit were aggressiveness, suicide attempts, suicidal ideation, and severe disruptive behavior requiring medical support. During their stay, the patients participated in group activities such as occupational therapy, art therapy, relaxation sessions, and sports in a small garden area outside the building, but with restricted access.

The diagnostic profile of the sample was based on Ref. [81] and is shown in Table 1.

Table 1: Diagnostic profile.

Number	*Percentage (%)*	*Diagnosis*
18	26.5	Affective bipolar disorder
12	17.6	Depressive disorder
10	14.7	Schizophrenia
8	11.8	Alcohol and drug dependence
4	5.9	Organic mental disorder
2	2.9	Personality disorders
14	20.5	Others

The scales used to convert the subjective variables, i.e., the psychomotor activity (X) and social interaction (Y) are based on [82] and are shown in Tables 2 and 3.

Table 2: Psychomotor activity (X).

Grade	***Description of the behavior***
1	Calm, adequate
2	Mild restlessness, noticed only when asked
3	Clearly uneasy, frequently walking around the ward
4	Severe agitation, disturbing other patients
5	Extreme excitation, needing sedation and/or physical restriction

Table 3: Social interaction (Y).

Grade	***Description of the behavior***
1	Active social contact, interacting with the other patients and staff
2	Mild tendency to socially withdraw, noticed only when asked
3	Clearly isolated, keeping some social contact with a few people
4	Severe social inhibition, keeping contact only when stimulated
5	Absence of verbal and non-verbal communication, catatonia

During the 62-day observation period, a daily grade was formulated as a composite pair (Y, X) of grades from the psychomotor (Table 2) and social interaction (Table 3) scales, and assigned to each patient, resulting in the creation of a matrix A to depict concurrent occurrences across the entire ward [39]. Each entry, denoted $a_{i,j}$, signifies the total number of grades in which (Y=i, X=j) within the observation period.

$$A = \begin{bmatrix} 270 & 259 & 212 & 109 & 29 \\ 170 & 98 & 56 & 16 & 8 \\ 100 & 65 & 21 & 8 & 9 \\ 9 & 9 & 6 & 0 & 1 \\ 4 & 8 & 0 & 0 & 0 \end{bmatrix}$$

Besides matrix A, Ref. [51] also provided another matrix, called ΔA, constructed by storing the total amount of absolute grade changes equal to $i - 1 = |\Delta Y| = |Y_1 - Y_2|$ and $j - 1 = |\Delta X| = |X_1 - X_2|$, respectively, in each entry $\Delta a_{i,j}$.

Changes were observed between two consecutive days over a period of 62 days. For example, if a patient experimented a variation from grade state (Y_1, X_1) to (Y_2, X_2) between the consecutive days, element $\Delta a_{|Y_1-Y_2|+1,|X_1-X_2|+1}$ is increased by one.

$$\Delta A = \begin{bmatrix} 439 & 347 & 80 & 19 & 5 \\ 198 & 122 & 38 & 10 & 3 \\ 35 & 27 & 8 & 3 & 0 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

Considering these data, it is possible to forecast and classify a pattern of dangerous days using a back-propagation Artificial Neural Network (ANN) [39] in a hypothetical scenario, which is further described in the text.

Such comprehension of the state of the ward is important for preparing the ward-staff action plan. In the example, the grades of interest are those with $X = 5$. Their occurrences require active action by the ward staff, with drug administration or physical restrictions on the patient.

To generate a time series of grade evolution, two other matrices are defined:

$$Q = (\sum_{i,j} a_{i,j})^{-1} A \qquad (6)$$

and

$$\Delta Q = (\sum_{i,j} \Delta a_{i,j})^{-1} \Delta A \tag{7}$$

In (6) and (7), matrix Q represents the relative frequency of each state, and ΔQ represents the relative frequency of each grade change.

Defining E_k as a possible state for a patient, $k = 1$ to 25, ordered with respect to a column of grades from matrix A, a transition between two states, E_{k1} to E_{k2}, occurs with a probability calculated as the joint probability of two independent events, i.e., choosing state E_{k2} and the grade differences between states.

To provide a quantitative treatment of this example, the transition probability between states is defined as

$$P(E_{k1} \to E_{k2}) = P(E_{k2}, |\Delta X_{k1,k2}|, |\Delta Y_{k1,k2}|) = P(E_{k2})P(|\Delta X_{k1,k2}|, |\Delta Y_{k1,k2}|) \tag{8}$$

Therefore, the transition matrix for a dynamic evolution between states can be derived using the probability of change as the coefficients of the state transition matrix [83]:

$$\phi_{k2,k1} = \Delta Q_{|Y_{k1}-Y_{k2}|+1,|X_{k1}-X_{k2}|+1} Q_{Y_{k2},X_{k2}} \tag{9}$$

Consequently, we define the temporal variable (t) as a day counting variable and S as a vector with 25 elements. In the vector, each entry contains the percentage of the total number of patients in the respective state. The equation of differences for the evolution of grades is

$$S(t+1) = \phi S(t) + S(t) \tag{10}$$

To illustrate these hypothetical state transition dynamics, a simulation using the state space presented in (10) was conducted for a random initial state $S(0)$. The system evolution was simulated for 1500 days, and the results for the grades of interest with $X = 5$ are shown in Figure 6.

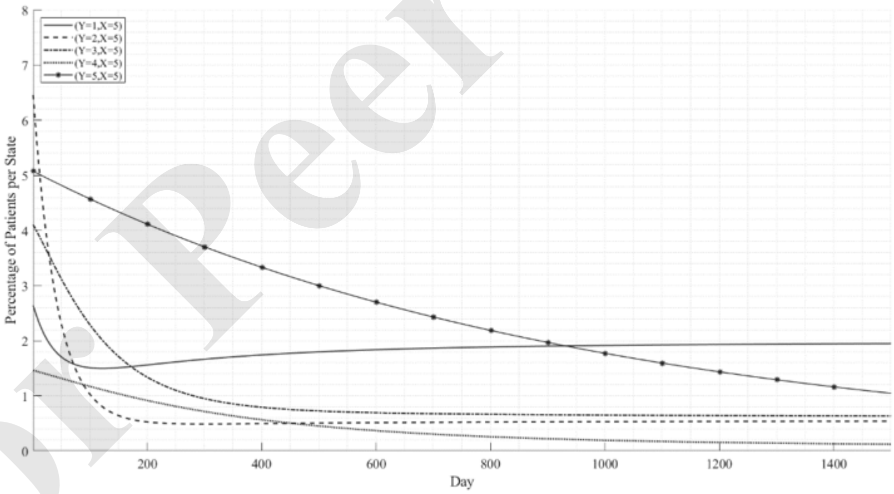

Figure 6: Daily evolution of percentage of grades.

As expected, in this particular case, the percentage of patients per state tends asymptotically to the values of relative occurrence. Thus, the dynamics are self-organized and stable [56]. Regardless of the classification criteria, all days are equally classified from a particular time. This results in the absence of a periodic dynamic pattern to forecast with an artificial intelligence algorithm, and the loss of the purpose of this example.

With the aim of inducing a periodic pattern in the system dynamics, amenable to prediction and classification, a set of constraints was imposed to alter the temporal evolution. These constraints include the following:

- Every day in which the state $(Y, X) = (1, 1)$ is found in the majority of patients, i.e., for the grade with the highest percentage of patients, $1/3$ of those patients are released.
- Subsequently, the same number of released patients are admitted, all in states with $X = 5$.
- The admission distribution by state respects the probability of occurrence of the state, represented in matrix Q.

Employing the above-stipulated premises, Figure 7 illustrates the temporal evolution of each daily grade. Within the identical simulation framework, the results of $X = 5$ are delineated in the context of Figure 6. Notably, discernible cyclic tendencies are observed for most of the grades, thereby affording the potential for predictive modeling using an Artificial Neural Network.

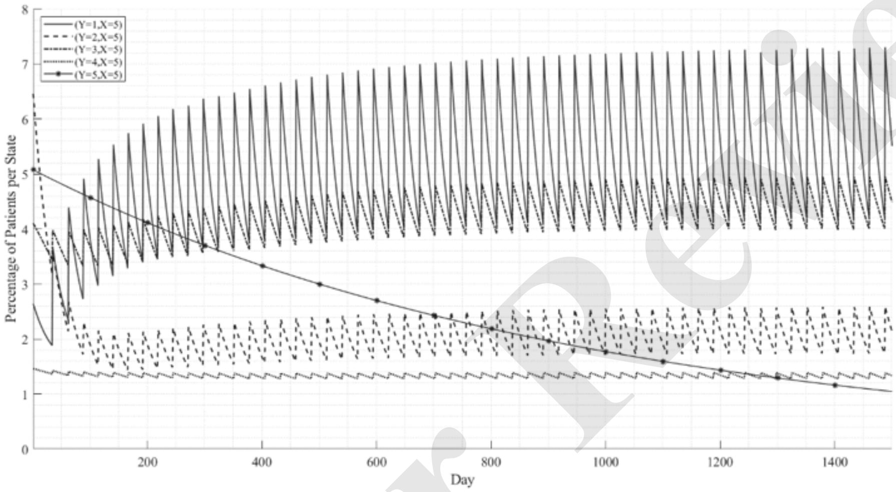

Figure 7: Daily grades with patient release and admission as described in the text.

To objectively define a dangerous day, a general grade, defined as the sum of the percentages of states with $X = 5$, was attributed to each day, considering the examples presented in Figures 7 and 8.

States with $X = 5$ were chosen to define dangerous days because, as previously stated, their occurrence dictates the active actions of the ward staff.

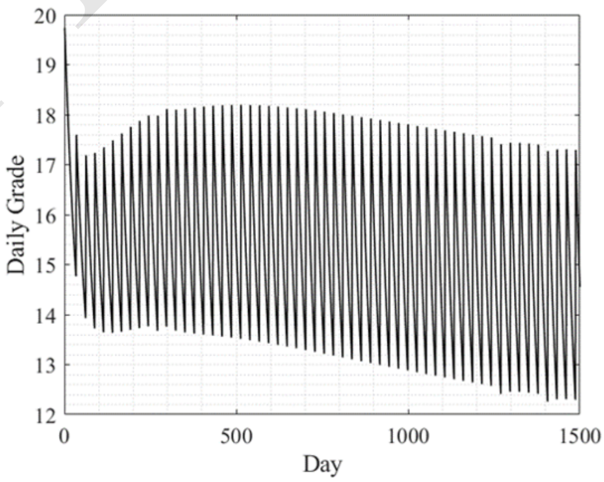

Figure 8: Daily grades with patient release and admission as described in the text.

Assuming a dangerous day as a day in which grade $X = 5$ exceeds 15%, to predict and classify the danger pattern, a backpropagation ANN was adapted from the source code proposed in [84].

A neural network was defined with a hidden layer containing eight neurons. For training, 65% of the generated time series was classified and used for 20000 epochs. The result presented in Figure 9 is a forecast of 450 days, with 4.57% false positives and 0% false negatives.

False positives are preferred to false negatives in intervention systems because they help ensure staff preparedness for potential interventions, which is critical for optimizing the overall ward performance.

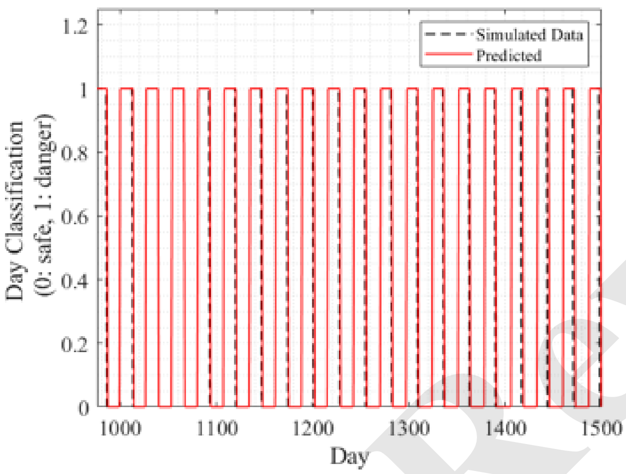

Figure 9: Daily classification forecast compared to the simulated time-series dangerousness.

This example demonstrates the effectiveness of using a quantitative approach in conjunction with machine learning to address a subjective problem objectively.

Prior knowledge of the dynamic behavior or operational modes of the ward is not required. Instead, by utilizing the available data and relevant quantitative parameters, the approach provides strong support for decision-making by the ward staff.

Moreover, using complexity measures, the complexity analysis of the system reveals that incorporating release and readmission procedures induces an oscillatory pattern in the LMC complexity measurement.

This periodic fluctuation in system complexity denotes a recurring variation in the amount of information present within the system. Consequently, it can be concluded that the ANN exhibits a remarkable performance because the periodic variation in information allows for effective training based on relevant information.

Conversely, in the absence of an admission and release procedure, the ANN has no periodic variation in the training data, resulting in a lack of relevant information to provide accurate predictions, except for trivial information.

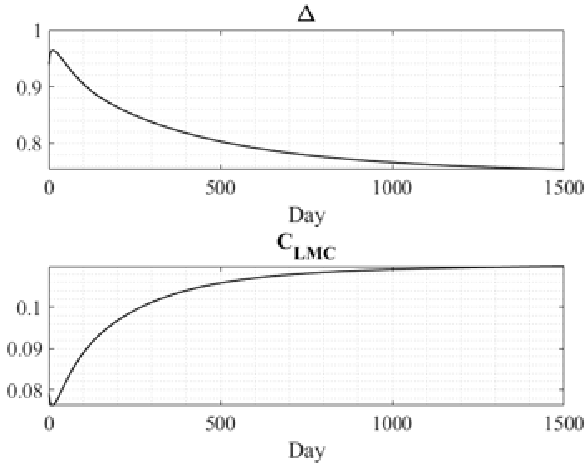

Figure 10: Relative disorder (Δ) and LMC complexity (CLMC) evolution during the days in the scenario without release and readmission.

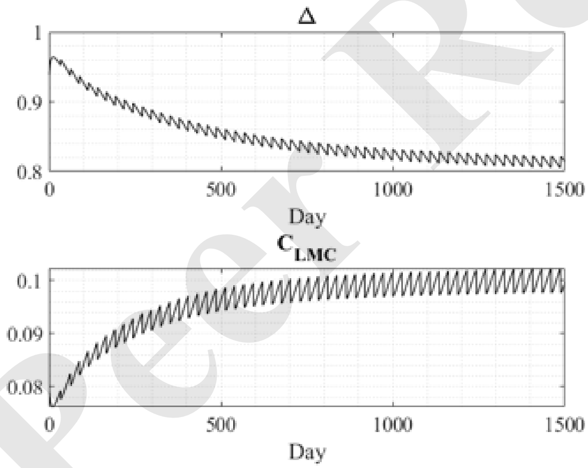

Figure 11: Relative disorder (Δ) and LMC complexity (CLMC) evolution during the days in the scenario with release and readmission.

6.2 Landscape complexity

The idea of evaluating landscape complexity is to extract information from remote sensor images to allow the measurement of complexity, considering the spatial heterogeneity grades shown by these images. The number of pixels associated with a digital state and its relative frequency were chosen as variables to input into equations (1) - (5).

The chosen theoretical assumption is that landscape patterns result from internal dynamical processes [85]. Consequently, evaluating the complexities of a landscape and its components can indicate integrity and resilience [86].

The automation of information calculation procedures from remote sensor images was initiated with the development of the *CompPlexus* program [87], dependent on the Envi® program to obtain the relevant data associated with the chosen image regions.

After this, QGIS *CompPlex HeROI*, *CompPlex Janus*, and *CompPlex Chronos* toolboxes were developed to evaluate regions of interest (ROIs) and obtain their complex signatures from an image or temporal series of images [86].

Using these programs and toolboxes, available at (https://github.com/lascaufscar/pyCompPlex), the important environmental problem of preserving river basins was addressed for the Ivinhema River, located in Mato Grosso do Sul state in the central region of Brazil.

The idea is to define the remaining native vegetation areas to protect the river basin by measuring their complexity patterns and collecting the image data available from the Brazilian Environment Ministry (http://geocatalogo.mma.gov.br).

CompPlex HeROI was used to evaluate the measures defined by equations (1) - (5) for regions selected from the RapidEye satellite images. The results are shown in Table 4.

It can be observed that the woods region called "MS157" presents, for the majority of bands and compositions, the lowest values for disorder measures (S, S_{max} and Δ) and the highest values for the real complexity measures (C_{LMC} and C_{SDL}), combining order and disorder.

This is an important qualitative result of the objective measures and suggests a way of preserving the entire system with decreasing diversity combined with increasing complexity due to human actions.

Another interesting result, shown in Figures 12 and 13, provides evidence that "Band 3" is the most effective frequency band to characterize a forest landscape.

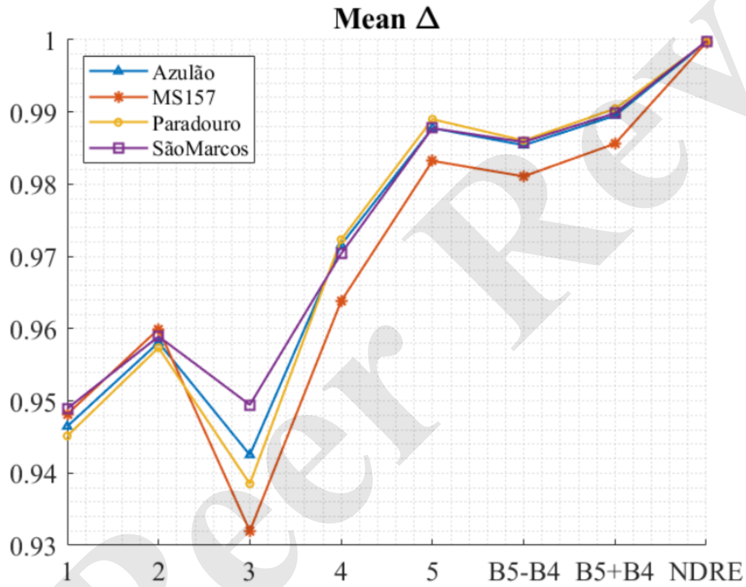

Figure 12: Region disorder measures depending on the sensor frequency band.

Table 4: Information and complexity measures (Borders of Ivinhema River – MS – Brazil).

Band	Region of Interest	Measure					Band	Region of Interest	Measure				
		He	Hmax	He/Hmax	SDL	LMC			He	Hmax	He/Hmax	SDL	LMC
1	Azulão#01	6,792464	7,179909	0,946038	0,051050	0,003665	5	Azulão#01	9,159228	9,273796	0,987646	0,012201	0,000317
	Azulão#02	6,799217	7,159871	0,949628	0,047834	0,003303		Azulão#02	9,158603	9,269127	0,988076	0,011782	0,000302
	Azulão#03	6,775995	7,179909	0,943744	0,053091	0,003647		Azulão#03	9,137857	9,252665	0,987592	0,012254	0,000316
	MS157#01	6,957021	7,330917	0,948997	0,048401	0,003051		MS157#01	9,035174	9,172428	0,985036	0,014740	0,000399
	MS157#02	7,031646	7,459432	0,942652	0,054059	0,003340		MS157#02	8,969456	9,124121	0,983049	0,016664	0,000465
	MS157#03	7,075787	7,426265	0,952806	0,044967	0,002775		MS157#03	8,834457	9,000000	0,981606	0,018055	0,000517
	Paradouro#01	6,819339	7,199672	0,947173	0,050036	0,003425		Paradouro#01	9,153739	9,271463	0,987302	0,012536	0,000324
	Paradouro#02	6,933362	7,348728	0,943478	0,053327	0,003532		Paradouro#02	9,170683	9,278449	0,988385	0,011480	0,000290
	Paradouro#03	6,891678	7,294621	0,944762	0,052187	0,003417		Paradouro#03	9,293519	9,375039	0,991305	0,008620	0,000210
	São Marcos#01	6,958585	7,357552	0,945775	0,051285	0,003278		São Marcos#01	9,112922	9,233620	0,986928	0,012901	0,000332
	São Marcos#02	7,382743	7,754888	0,952012	0,045686	0,002463		São Marcos#02	9,203221	9,310613	0,988466	0,011401	0,000293
	São Marcos#03	7,260766	7,651052	0,948989	0,048409	0,002761		São Marcos#03	9,147723	9,259743	0,987902	0,011951	0,000304
2	Azulão#01	7,457993	7,794416	0,956838	0,041299	0,002172	B5-B4	Azulão#01	9,036264	9,172428	0,985155	0,014624	0,000392
	Azulão#02	7,471047	7,768184	0,961749	0,036787	0,001903		Azulão#02	9,045538	9,184875	0,984830	0,014940	0,000407
	Azulão#03	7,436417	7,781360	0,955671	0,042364	0,002168		Azulão#03	9,077883	9,204571	0,986236	0,013574	0,000357
	MS157#01	7,422917	7,741467	0,958852	0,039455	0,002037		MS157#01	8,884691	9,044394	0,982342	0,017346	0,000482
	MS157#02	7,352594	7,665336	0,959201	0,039135	0,002098		MS157#02	8,896821	9,057992	0,982207	0,017477	0,000500
	MS157#03	7,399540	7,693487	0,961793	0,036748	0,001923		MS157#03	8,758025	8,948367	0,978729	0,020819	0,000627
	Paradouro#01	7,350534	7,679480	0,957166	0,041000	0,002226		Paradouro#01	9,022756	9,167418	0,984220	0,015531	0,000428
	Paradouro#02	7,444855	7,787903	0,955951	0,042108	0,002197		Paradouro#02	9,105607	9,228819	0,986649	0,013173	0,000343
	Paradouro#03	7,565056	7,888743	0,958968	0,039348	0,001935		Paradouro#03	9,160561	9,278449	0,987294	0,012544	0,000341
	São Marcos#01	7,446766	7,768184	0,958624	0,039664	0,002066		São Marcos#01	9,037050	9,184875	0,983906	0,015835	0,000442
	São Marcos#02	7,628992	7,936638	0,961237	0,037260	0,001810		São Marcos#02	9,150485	9,266787	0,987450	0,012393	0,000325
	São Marcos#03	7,452275	7,787903	0,956904	0,041239	0,002140		São Marcos#03	9,072654	9,199672	0,986193	0,013616	0,000360
3	Azulão#01	6,905711	7,321928	0,943155	0,053614	0,003536	B5+B4	Azulão#01	9,24851373	9,34207	0,98998	0,00991	0,00025
	Azulão#02	6,735231	7,149747	0,942024	0,054615	0,003950		Azulão#02	9,19556759	9,3015	0,98861	0,01126	0,00029
	Azulão#03	6,648753	7,055282	0,942379	0,054300	0,004091		Azulão#03	9,24119825	9,33539	0,98991	0,00999	0,00025
	MS157#01	6,479446	6,930737	0,934886	0,060875	0,004809		MS157#01	9,02304415	9,15987	0,98506	0,01471	0,0004
	MS157#02	6,415515	6,906891	0,928857	0,066082	0,005213		MS157#02	9,10401857	9,224	0,98699	0,01284	0,00033
	MS157#03	6,586924	7,066089	0,932188	0,063214	0,004573		MS157#03	9,01815231	9,15735	0,9848	0,01497	0,00041
	Paradouro#01	6,546897	7,011227	0,933773	0,061841	0,004860		Paradouro#01	9,20899785	9,31288	0,98885	0,01103	0,00028
	Paradouro#02	6,731903	7,159871	0,940227	0,056200	0,004004		Paradouro#02	9,27725012	9,36851	0,99026	0,00965	0,00025
	Paradouro#03	6,778799	7,199672	0,941543	0,055040	0,003815		Paradouro#03	9,32605709	9,39874	0,99227	0,00767	0,00018
	São Marcos#01	6,867165	7,247928	0,947466	0,049774	0,003441		São Marcos#01	9,21183658	9,30834	0,98963	0,01026	0,00025
	São Marcos#02	6,887667	7,247928	0,950295	0,047235	0,003290		São Marcos#02	9,28206445	9,36632	0,991	0,00891	0,00022
	São Marcos#03	6,786834	7,139551	0,950597	0,046963	0,003348		São Marcos#03	9,22287615	9,32643	0,9889	0,01098	0,00028
4	Azulão#01	8,284628	8,531381	0,971077	0,028086	0,001019	NDRE	Azulão#01	9,608645	9,611025	0,999752	0,000248	0,000006
	Azulão#02	8,234723	8,467606	0,972497	0,026746	0,000980		Azulão#02	9,601955	9,607330	0,999440	0,000559	0,000016
	Azulão#03	8,251655	8,495855	0,971257	0,027917	0,001017		Azulão#03	9,612159	9,612868	0,999926	0,000074	0,000002
	MS157#01	7,878033	8,149747	0,966660	0,032229	0,001377		MS157#01	9,600992	9,605480	0,999533	0,000467	0,000011
	MS157#02	7,747349	8,055282	0,961772	0,036766	0,001667		MS157#02	9,609608	9,611025	0,999853	0,000147	0,000003
	MS157#03	7,803447	8,103288	0,962998	0,035633	0,001640		MS157#03	9,599404	9,603626	0,999560	0,000439	0,000010
	Paradouro#01	8,269737	8,491853	0,973844	0,025472	0,000942		Paradouro#01	9,599404	9,605480	0,999367	0,000632	0,000018
	Paradouro#02	8,306431	8,543032	0,972305	0,026928	0,000975		Paradouro#02	9,607057	9,609179	0,999779	0,000221	0,000005
	Paradouro#03	8,470220	8,724514	0,970853	0,028297	0,000965		Paradouro#03	9,609608	9,611025	0,999853	0,000147	0,000003
	São Marcos#01	8,203993	8,455327	0,970275	0,028841	0,001053		São Marcos#01	9,604506	9,607330	0,999706	0,000294	0,000006
	São Marcos#02	8,384526	8,614710	0,973280	0,026006	0,000896		São Marcos#02	9,609608	9,611025	0,999853	0,000147	0,000003
	São Marcos#03	8,205244	8,479780	0,967625	0,031327	0,001175		São Marcos#03	9,609608	9,611025	0,999853	0,000147	0,000003

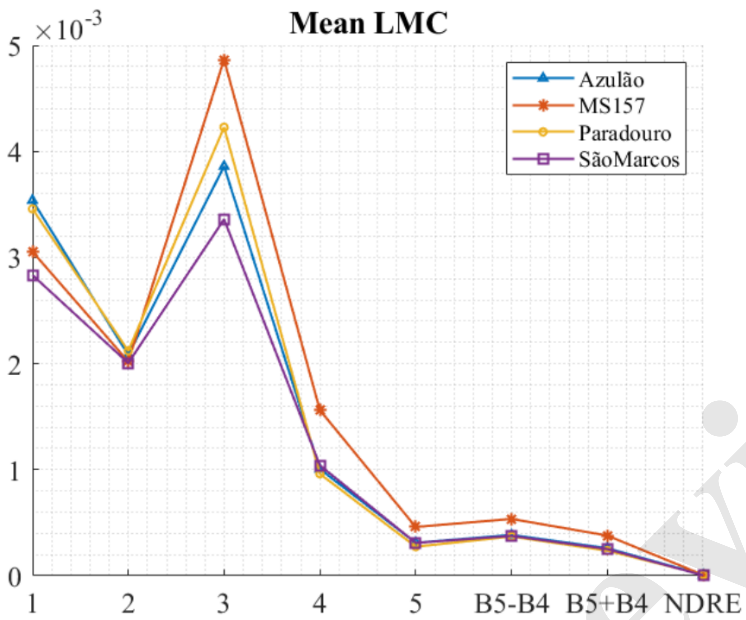

Figure 13: Region LMC complexity measures depending on the sensor frequency band.

7 Conclusions

As shown throughout this text, Complexity Engineering represents a new, more systemic and integrative way of thinking and doing Engineering. Its applications range from a new way of interpreting classic Engineering problems, as illustrated by the example of Elevado João Goulart, to problems in more recent areas of Engineering, such as biomedical and environmental issues. From the first case, it can be concluded that an engineering project cannot disregard the context in which it is inserted and, therefore, cannot escape the non-linearities and uncertainties involved in this process. The other two last examples presented here show that the same concept (information entropy) and measures derived from it can be used for very different problems, but that they are part of the same category of problems and the same way of interpreting them: 'wicked problems' evaluated from Complexity Engineering.

Concerning the new ways of engineering, this study is a manifesto of an open-minded view combining machine learning with complexity measures, combining artificial intelligence from Turing and information theory developed by Shannon. The diversity of the applications presented here, ranging from behavioral to environmental issues, confirms the importance of thinking about new technological developments beyond trivialities, seeking human enhancement, and preserving the planet and its life diversity.

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