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Using Artificial Intelligence to Assist Tree Risk Assessment

By Steffen Rust and Bernhard Stoinski

Abstract. Although the industry has raised the standards of tree risk assessment considerably in recent years, the quality of judgements is still very variable and influenced by a wide range of factors. Due to the complexity and diversity of trees and sites, collecting and verifying relevant personal experiences takes tree assessors many years. In many countries, new tree assessors learn from a small number of experienced peers. Artificial intelligence (AI) can be used to collect and condense scattered knowledge and deploy it in a support tool for basic tree assessment. In this project, the application of a commercial AI decision-making system software (Dylogos) to tree assessment is tested. The software is based on a new dynamic nonclassical logic, which combines diverse knowledge sources to an emergent system to support visual tree assessments. A set of rules describes existing knowledge about the mostly unsharp parameters affecting the likelihood of failure and damage. The software evaluates the data collected during a basic tree assessment and provides an estimate of the level of risk posed by the tree. The result and the reasons for it are presented in plain language. Users can then examine this estimate and feed their own assessment back into the system to train it further, so that this "white" AI system is self-learning based on experience acquired in practical use. The use of AI in tree risk assessment not only supports the user but can also be used to disseminate knowledge and promote the standardization of decision-making in tree assessment. Important directions for further research and knowledge gaps related to the training of AI systems in the absence of industry-wide, agreed-upon criteria for risk identified in this project are: how to collect sufficient quality-assured data sets to define the initial set of rules; and how to assess the level of expertise of users training the system further.

Keywords. Artificial Intelligence; Fuzzy Logic; Tree Inventory; Tree Risk Assessment.

INTRODUCTION

Urban trees, their sites, and potentially affected targets are highly variable, and accidents caused by failing trees or parts of them are very rare (Watt and Ball 2009; Dunster 2014), so few tree risk assessors will experience the failure of a representative number of trees after they have assessed them. Therefore, decisions of early career tree assessors are rarely based on their own experience.

Even if tree assessors systematically collect feedback from felled trees or advanced assessments, few but the most obvious criteria for hazardous trees are universally accepted, and many aspects of tree assessment still lack a rigorous scientific basis (Wagener 1963; Smiley and Fraedrich 1992; Mattheck et al. 1994; Niklas and Spatz 2000; Kane et al. 2001; Mattheck et al. 2002; Kane and Ryan 2003, 2004; Matheny and Clark 2009; Rust et al. 2011; Rust 2012; Jillich et al. 2013; Spatz and Niklas 2013; Ciftci, Arwade, et al. 2014; Ciftci, Kane, et al. 2014; Böttcher et al. 2016; Slater 2016, 2021).

Consequently, novice tree risk assessors often rely on skills handed down from a limited number of more or less experienced colleagues who transfer their intuitions to the next generation. Even amongst trained industry professionals, there is a significant level of variation regarding their assessment of likelihood of impact ratings, likelihood of failure ratings, and consequences of failure ratings (Stewart et al. 2013; Koeser and Smiley 2017).

Several institutions have developed guidance and certification programs in order to raise the standards of training in and practice of tree assessment (Norris and Moore 2020), e.g., ISA's Tree Risk Assessment Qualification (TRAQ)(Dunster et al. 2013) or FLL in Germany (FLL 2004). Although this will almost certainly have raised the standards of tree risk assessment (Koeser and Smiley 2017), the restrictions outlined above still apply. Decision-support systems can assist tree risk assessors in several ways:

- They collect knowledge from experts and make it available to a wide range of users.
- They focus attention.
- They help to standardize the decision-making process.

The objectives of this research are to determine how an innovative artificial intelligence (AI)-based approach could be applied to tree assessment and to identify relevant knowledge gaps.

A standardized assessment of trees as living systems is difficult for various but obvious reasons. Nature and natural systems are always dynamic and subject to changes. The general dynamic logic (GDL) is a logic that is formulated with axioms in natural language rather than algorithms. It allows to build comprehensive causal chains consisting of variables with associated adjectives. These adjectives bring in the dynamic element.

The challenge in assessing the overall tree system lies in the characteristics of the parameters used to describe the system. Only a few of the parameters are physically measurable, e.g., diameter, height, or the occupancy rate. For some of the parameters, the effort involved does not justify the benefit of precision (trunk or branch diameter, crown density), while the measurement of others vastly exceeds the time usually spent at a tree for a basic assessment (leaf area, wind load, occupancy rate). Most characteristics used to assess the tree and the risks it might present are based on visual observations made by a human assessor. The observations and the intuition involved will be a direct reflection of the experience and the knowledge of the assessor.

Even if every single parameter on its own indicates a safe tree, the overall impression of a tree can be different. Malcolm Gladwell stated this in his book *Blink: The Power of Thinking Without Thinking* (2005). In the first chapter, it describes how experts intuitively and very quickly had a doubt about the authenticity of an object without being able to clearly indicate why, the object in question being the kouros of the Getty Museum. A detailed and long-lasting analysis by several other experts resulted in the conclusion that the object was authentic. Only later, a second identical object appeared on the market and eventually the kouros was identified as having been made in the 20th century. The point that the author makes in the book is that experts with a wealth of knowledge can trust their intuitive assessment without first having to pinpoint the details of why this is. The overall picture gave the reason for doubt while the investigation that looked at known attributes failed. Doubting provided reasons for looking further and deeper to understand and to dig out the objective points.

A tree assessment system that aims to use the knowledge and the intuition of an experienced and knowledgeable assessor needs to be able to capture the nonmeasurable values in a meaningful way, leaving precision aside.

The mapping of these uncertainties into a mathematical model that allows a standardization of the assessment is the subject of this work and the central core of the AI-software decision system.

In the following, dynamic logic is presented as an innovative tool that provides a solution for bringing together the two diverging areas of both fuzzy descriptive parameters and a standardization of assessment results.

THE GENERAL DYNAMIC LOGIC

The general dynamic logic (GDL) is a system of knowledge-based modules using axiomatic linguistic structures that are filled with specific detailed knowledge. Each of the modules can be used by itself, but they can also be combined and linked. With the modules, we build the model of our specific topic or business case, incorporating our nonmeasurable characteristics in the form of fuzzy sets.

Due to the axiomatic linguistic structure, all axioms within the calculus are not formulated as mathematical formulas, but as meaningful text and thus comprehensible. This is the fundamental difference to neural networks where decision-making is not directly comprehensible. Neural networks are therefore referred to as “Black AI.” The GDL with an axiomatic structure belongs to the group of “White AI.”

Fuzzy logic will not be discussed in detail here. If desired, please refer to: Zadeh 1965, 1971; Mac Lane 1978; Dubois and Prade 1980; Mamdani and Gaines 1981; Bothe 1993; Kosko and Toms 1993.

MODELLING TREE ASSESSMENT IN THE GENERAL DYNAMIC LOGIC

As the example of the kouros shows, a model description consists not only of measurable, but also of many nonmeasurable, parameters and an overall impression.

The overall impression in a tree assessment results from fuzzy facts that can only be described or estimated. Taking the example of wind load and its impact, such parameters might be exposure, crown area, shape, density, height, mechanical defects, and stress raisers. Provided this assessment is made by an experienced and knowledgeable person, we can assume that it has a high probability to be true. An expert will make many such estimates in the shortest possible time and relate them to each other intuitively and as best as possible.

How does this work? The assessor doing a visual assessment does not think about specific measured values but rather considers different elements that can only be estimated and groups them together, e.g., wind load (site, size, and shape of the tree) and load-bearing capacity (stem and branch dimensions, mechanical defects, stress raisers). This process links together supposedly disjunctive values and makes them available as a basis for decision-making.

This combination of nonmeasurable elements is done with a commercial AI software (Dylogos) that is already used in projects in other areas using the GDL.

It builds causal chains to form a statement. The GDL enables this grouping through sets and the formation of a causal chain. The sets are connected by means of operators, such as "AND" and "OR" and negation in natural linguistic statement chains that lead to an implication. The elements and the structuring are originally defined by the user but can be modified and added to. The artificial intelligence will build and optimize the causal chains and the conclusions made. Connecting the software to an existing risk assessment database will help build the robust expertise that makes the conclusions reliable and facilitates the learning process of the AI part. How individual elements are impacting the result or how the system gets to the result is transparent at any time.

Assessing Tree Load (Simplified and Limited Model)

Mechanical load is a key parameter for the assessment of the likelihood of failure of a tree or a part of it (Morgan and Cannell 1987; Cannell and Morgan 1989; Wessolly and Erb 1998; Bond 2011a, 2011b, 2012; Dahle et al. 2017). Unlike other outcomes of tree assessments, it is rated on an ordinal scale, as opposed to the logarithmic scales likelihoods are based on. To simplify the mathematical outline of the method further, we are limiting the description to a small subset of characteristics used to assess the load, which itself depends on several factors including exposure (wind zone, terrain, site), area (foliage, branches), and lever arm (tree height, branch length). All have in common that they are not precisely measurable.

Defining a Fuzzy Set

The assessment of the lever arm can be standardized by a mathematical procedure of fuzzy set formation.

The parameter "lever arm" does not represent a quantity with an estimated value in the sense of fuzzy logic but rather is modelled as overlapping symmetric triangular distributions of truth-values, which are the classic representation of a fuzzy set (Figure 1).

With the help of adjectives that function as connotations of the term "lever arm," we can define its size. The adjectives "extreme," "long," "medium," and "short" shall serve as examples.

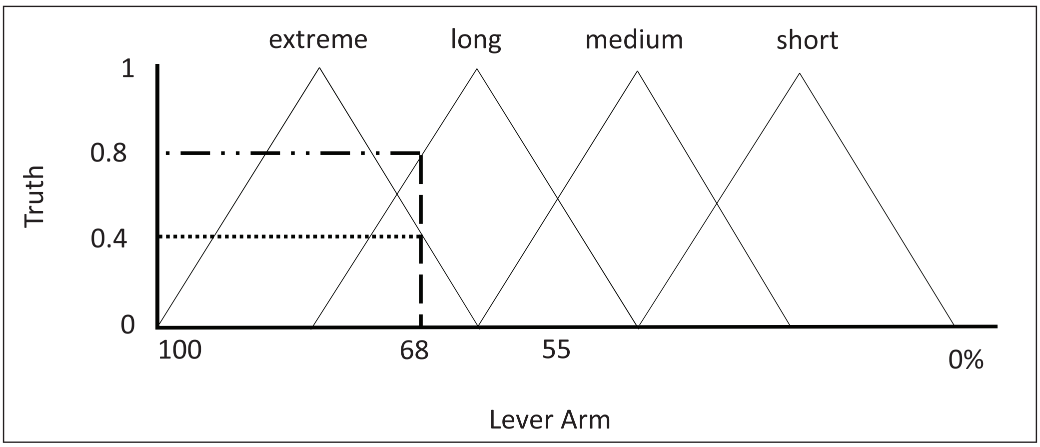

Figure 1. Set formation of lever arm.

Figure 1 shows the special feature of fuzzy logic and its performance. A given lever arm, here of relative size 68%, can be affiliated with two truth-values (here: 0.4 and 0.8). For this exemplary tree, one assessor might conclude that the lever arm is just "long," while another might estimate that the lever arm is rather "extreme."

In the following, the creation of the variable "wind exposure" in the software shall serve as an example to illustrate the process. The variable is to be defined by means of the set designations "protected," "partial," "full," and "wind funneling" (Figure 2).

Estimates as Quantifiable Variables

In the field of tree assessment, many variables can only be estimated. The method of assigning an estimate in the GDL to a numerical value was shown in the previous section. In the software, the input is done via sliders or trackbars in addition to the set labels. Figure 3 shows this in the simplified model.

From Sets to Causal Logical Chains

The sets have a further significance. With the sets, we build causal logical chains that imply a solution. For the formation of a propositional causal chain, the assessment of "wind exposure," as well the other parameters, is to be defined analogously to the lever arm by means of fuzzy sets. These causal chains form a decision tree. The parameter "load" in Table 1 is a node of the decision tree from which the respective causal chain branches off. Typical causal chains can then be built as illustrated in Table 1.

The formation of the implication is done by the max-min operator. When all parameters have been similarly calculated using these max-min operators, we can obtain the overall truth-value of an axiom. And finally, the sum of all axioms builds the calculus that will have a truth-value of its own. This value may be taken as an expression of the reliability of the statement.

The total truth-value (membership) of the calculus is determined as the mean value of the sum of all truth-values divided by the total number of all rules.

From Causal Chain to Conclusion Statement

In the GDL, each variable can now be given a weighting. This in turn results in a weighting of the statement within the axiomatic causal chain.

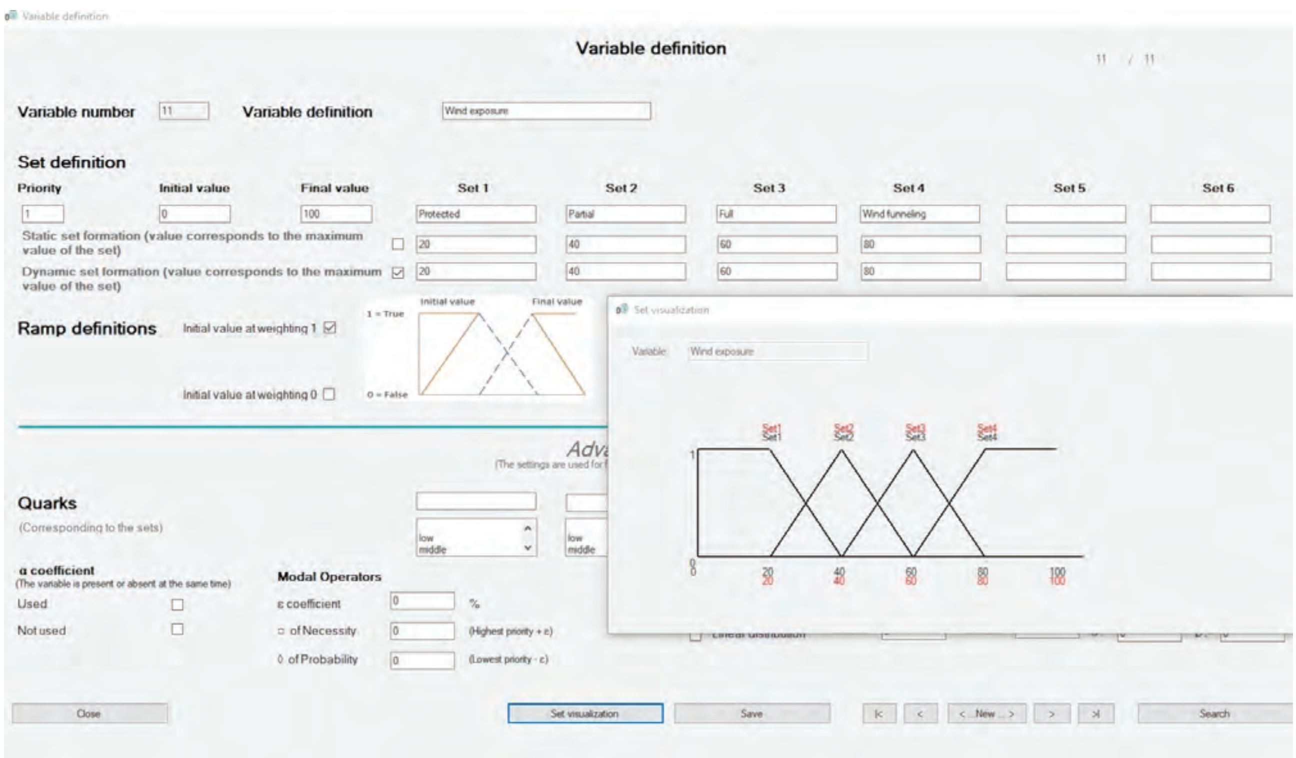

Figure 2. Creation of the variable "wind exposure."

Table 1. Example of a logical axiom with *n* parameters and *m* rules.

	If Parameter 1		Parameter 2		Parameter 3		Parameter *n*		Conclusion
Rule 1	Wind exposure (protected)	AND	Surface area (normal)	AND	Lever arm (short/pruned)	AND	…	THEN	Load (low)
Rule 2	Wind exposure (partial)	AND	Surface area (low)	AND	Lever arm (normal)	AND	…	THEN	Load (medium)
Rule 3	Wind exposure (full)	AND	Surface area (high)	AND	Lever arm (long)	AND	…	THEN	Load (extreme)
Rule 4 to *m*	… …	AND	… …	AND	… …	AND	… …	THEN	Load …

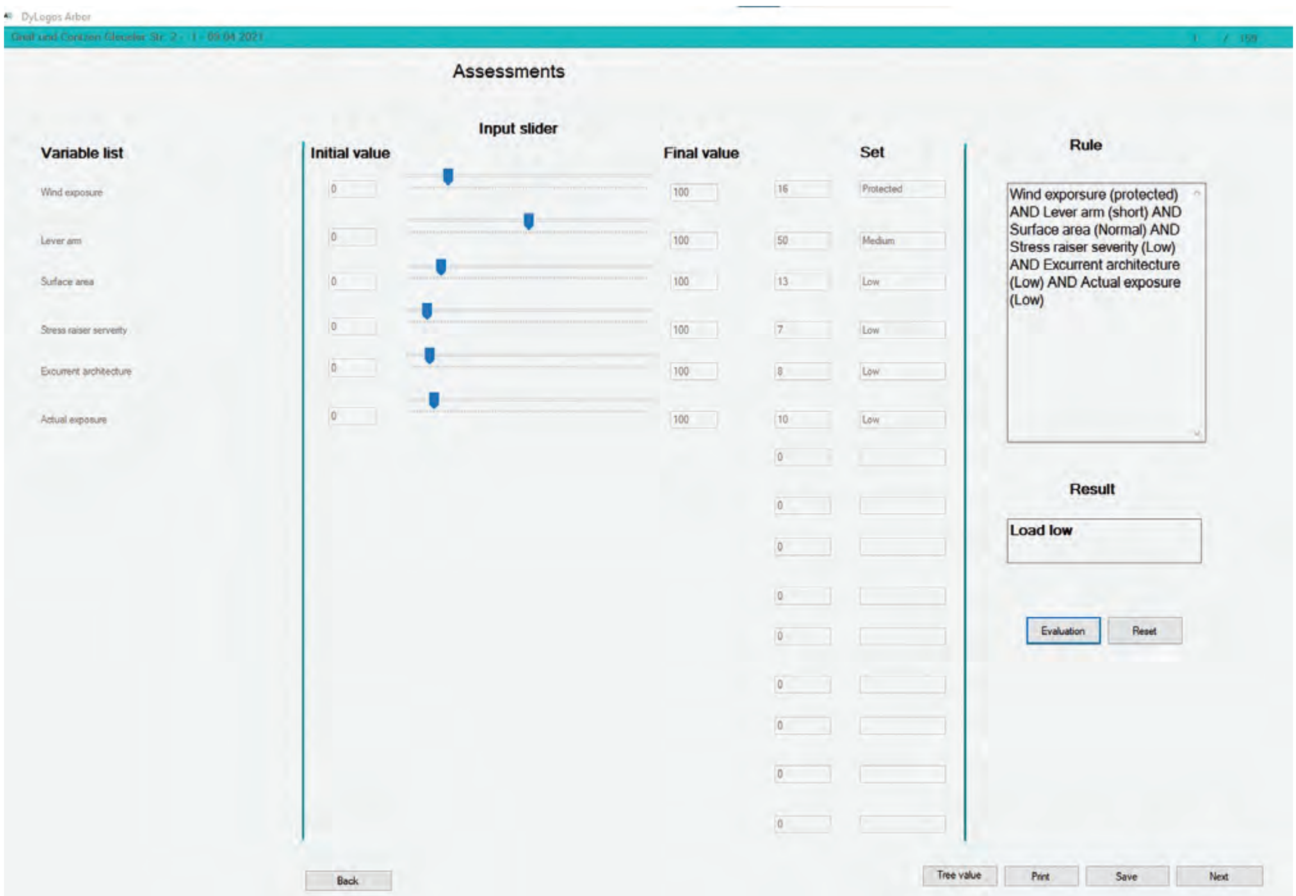

Figure 3. Assessment of tree load with trackbars, based on Bond 2011b.

A truth-value of 1 would correspond to a 100% result, which means that the statement is always true. In practice, it is common knowledge that results with a plausibility of 95% are accurate.

LEARNING FROM PLAUSIBILITY/METASYSTEM

Initial Set of Rules

First, the system supports users by applying the axioms defined by its developers, based on their experience and

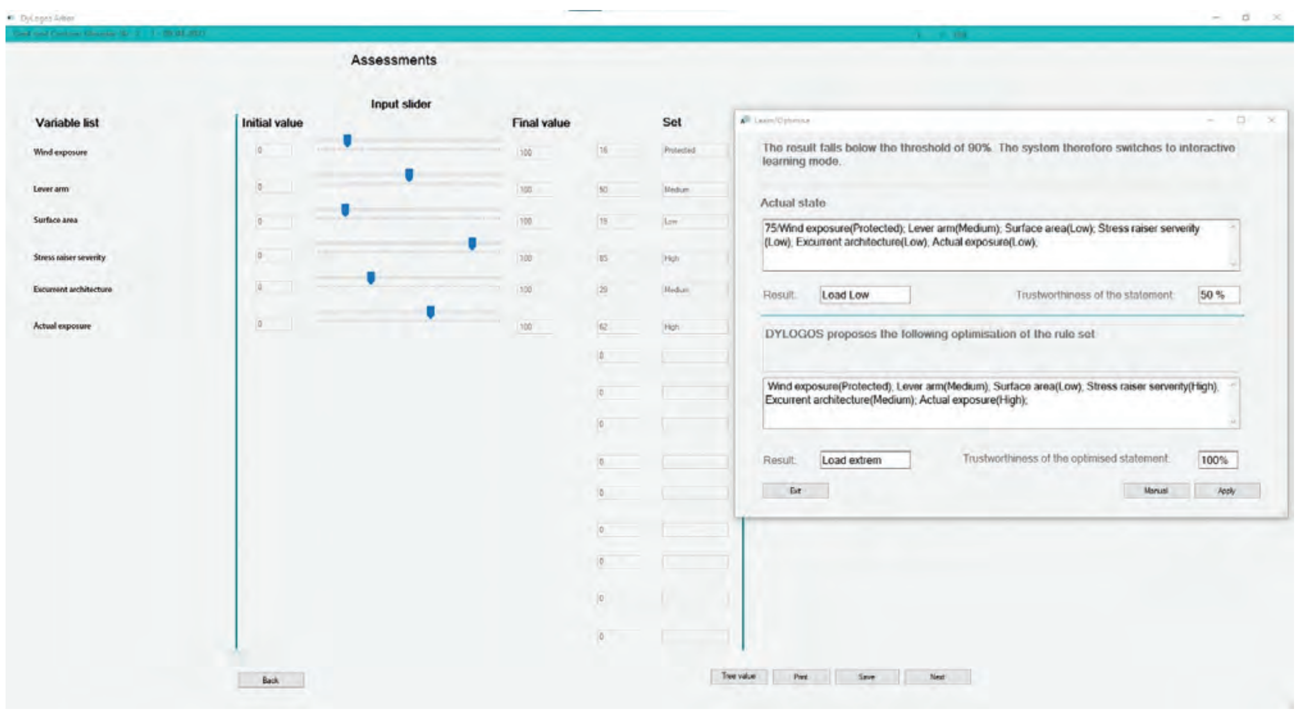

Figure 4. Learning mode.

further valuable sources of information, like tree failure databases (Matheny et al. 2006; Hartley and Chalk 2019) and compilations (Lonsdale 1999), which can be used to derive species profiles to aid the assessment.

Clearly, further scientific work with industry organizations and experts is needed to build the standard from which the system will start. We propose three ways to collect this knowledge:

- evaluation of data sets containing basic and advanced assessments of the same tree
- workshops with experienced tree assessors assessing defined sets of trees
- questionnaires

Learning

During its use, the system is capable of learning. In all the characteristics that are highly reliant on the knowledge and experience of the assessor, we find two sets of fuzziness: that of the assessed characteristic and that of the assessor's quality. Each user will be ranked in a range from absolute beginner to expert.

This point is important. The system must only learn from an expert and not only support, but also guide, the nonexpert.

The GDL provides an acceptance threshold below which the learning mode is activated (Figure 4). Learning takes place in interaction with the user. At this point, we come back to the human factor. A low truth-value, like the accuracy rate from a confusion matrix of the calculus, is the equivalent of a result that has a low trustworthiness.

Earlier, we referred to the differences in knowledge of individuals that may be using the system. Who should be allowed to train the system? The problem behind this question is the way the system learns. Because of the interactive way in which the system learns through the user, there is a danger that the system will dilute knowledge acquired, for example, when used by a layperson. The system should only learn from users who have proven that they are qualified to ensure the quality of the data that will in turn provide the support a less experienced person may need to get the second opinion.

Here, we are getting to a point that is critical and still unsolved in the AI science in general. The discussion is just beginning. Different approaches are thinkable. In our case, users could be considered qualified based on their professional qualifications, on years of practical work experience, and/or on a test to be performed when starting to use the application.

In addition to the learning from the usage, the software contains an additional meta-level. This meta-level is needed to organize optimization tasks, as well as error handling. A complex set of rules can and will be error-prone. The metasystem contains general statements on how to deal with such errors.

The metasystem contains axiomatic statements that can lead to the creation of axioms in the execution layer, as well as their optimization. The formal languages used are independent of each other, which means that statements of the metasystem only affect the execution layer and not the solution space. Conversely, the implications of the axiomatic causal chains have no influence on the metasystem.

CONCLUSIONS

In the risk assessment of a complex living organism, such as a tree, few measurable and many nonmeasurable parameters interact. In the case of nonmeasurable parameters, the impact of the expert's intuition is high. Therefore, the assessment can lack robustness, credibility, and repeatability, 3 of 8 criteria for the effectiveness of risk assessment methods identified in earlier studies (Norris 2007). By splitting up larger problems into sets of smaller problems, the system presented guides the user's attention, making them aware of otherwise implicit assumptions, and thus increasing robustness and credibility.

By forming fuzzy sets, statements relating to nonmeasurable fuzzy parameters of intuition are mathematically standardized to increase repeatability.

Furthermore, the results obtained via the fuzzy sets can be connected via a calculus that incorporates the expert's knowledge. By using the GDL as an AI system, the quality of stored knowledge is constantly checked and improved when using the system. The experience of many tree assessors gained over years is made available to support novice tree assessors.

In this project, we provide a proof of concept of an AI system for tree risk assessment. The gaps in our knowledge identified here, especially the lack of universally accepted and scientifically proven rules, are not limited to the use of artificial intelligence, but are relevant to tree assessment at large. A broad discussion of the rules that would be accepted in AI systems will also improve conventional tree assessment.

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Résumé. Bien que l'industrie ait considérablement rehaussé les normes d'évaluation des risques liés aux arbres au cours des dernières années, la qualité des jugements est encore très variable et demeure influencée par un large éventail de facteurs. Du fait de la complexité et de la multiplicité des arbres et des sites, l'apprentissage et la validation des expériences personnelles pertinentes prennent de nombreuses années aux évaluateurs d'arbres. Dans plusieurs pays, les évaluateurs débutants apprennent auprès d'un petit nombre de pairs expérimentés. L'intelligence artificielle (IA) peut être mise à contribution afin de rassembler et concentrer des connaissances éparses et les déployer dans un outil d'aide à l'évaluation élémentaire des arbres. Dans ce projet, l'application d'un logiciel commercial décisionnel d'IA (Dylogos) à l'évaluation des arbres a été mise à l'essai. Le logiciel repose sur une nouvelle logique dynamique non classique, combinant diverses sources de connaissances en un système émergent afin de soutenir l'évaluation visuelle des arbres. Une série de règles décrit les connaissances existantes sur les paramètres, pour la plupart imprécis, qui influent sur la probabilité de défaillance et de dommages. Le logiciel évalue les données recueillies lors d'une évaluation fondamentale de l'arbre et génère une estimation du niveau de risque que l'arbre présente. Le résultat et les justifications qui l'expliquent sont présentés en langage clair. Les usagers peuvent alors analyser cette estimation et intégrer leur propre évaluation dans le système pour le parfaire davantage, de sorte que ce système d'IA "blanc" est un système d'auto-apprentissage basé sur l'expérience acquise dans la pratique. L'utilisation de l'IA dans l'évaluation des risques liés aux arbres ne soutient pas seulement l'usager, mais peut également servir à généraliser les connaissances et à promouvoir la normalisation dans la prise de décision lors de l'évaluation des arbres. Les pistes importantes pour la poursuite des recherches et des lacunes dans le savoir lié à la formation des systèmes d'IA, en l'absence de critères de risque convenus à l'échelle de l'industrie, identifiées dans ce projet sont les suivantes: comment recueillir des groupes de données d'une qualité suffisante afin d'établir la série initiale de règles et comment évaluer le niveau d'expertise des utilisateurs qui alimentent le système.

Zusammenfassung. Obwohl die Branche in den letzten Jahren die Standards für Baumrisikobewertungen erheblich angehoben hat, ist die Qualität der Beurteilungen immer noch sehr unterschiedlich und wird von einer Vielzahl von Faktoren beeinflusst. Aufgrund der Komplexität und Vielfalt von Bäumen und Standorten benötigen Baumgutachter viele Jahre, um einschlägige persönliche Erfahrungen zu sammeln und zu überprüfen. In vielen Ländern lernen neue Baumgutachter von einer kleinen Anzahl erfahrener Kollegen. Künstliche Intelligenz (KI) kann eingesetzt werden, um verstreutes Wissen zu sammeln und zu verdichten und es in einem Hilfsmittel für die grundlegende Baumbewertung einzusetzen. In diesem Projekt wird die Anwendung einer kommerziellen KI-Entscheidungssystemsoftware (Dylogos) für die Baumbewertung getestet. Die Software basiert auf einer neuen dynamischen, nicht-klassischen Logik, die verschiedene Wissensquellen zu einem emergenten System zur Unterstützung visueller Baumbewertungen kombiniert. Ein Regelwerk beschreibt das vorhandene Wissen über die meist unscharfen Parameter, die die Ausfall- und Schadenswahrscheinlichkeit beeinflussen. Die Software wertet die bei einer grundlegenden Baumbeurteilung gesammelten Daten aus und liefert eine Einschätzung des Risikogrades, den der Baum darstellt. Das Ergebnis und die Gründe dafür werden in verständlicher Sprache dargestellt. Die Nutzer können diese Einschätzung überprüfen und ihre eigene Einschätzung in das System einspeisen, um es weiter zu trainieren, so dass dieses "weiße" KI-System auf der Grundlage der in der Praxis gewonnenen Erfahrungen selbstlernend ist. Der Einsatz von KI bei der Risikobewertung von Bäumen unterstützt nicht nur den Benutzer, sondern kann auch zur Verbreitung von Wissen und zur Förderung der Standardisierung der Entscheidungsfindung bei der Baumbewertung genutzt werden. In Anbetracht des Fehlens branchenweit vereinbarter Risikokriterien wurden in diesem Projekt folgende wichtige Richtungen für die weitere Forschung und Wissenslücken im Zusammenhang mit der Schulung von KI-Systemen ermittelt: Wie können ausreichende qualitätsgesicherte Datensätze gesammelt werden, um die anfänglichen Regeln festzulegen, und wie kann der Kenntnisstand der Benutzer, die das System weiter schulen, bewertet werden?

Resumen. Aunque la industria ha elevado considerablemente los estándares de evaluación del riesgo de los árboles en los últimos años, la calidad de los juicios sigue siendo muy variable e influenciada por una amplia gama de factores. Debido a la complejidad y diversidad de árboles y sitios, recopilar y verificar experiencias personales relevantes lleva muchos años a los evaluadores de árboles. En muchos países, los nuevos evaluadores de árboles aprenden de un pequeño número de pares experimentados. La inteligencia artificial (IA) se puede utilizar para recopilar y condensar conocimiento disperso y desplegarlo en una herramienta de apoyo para la evaluación básica de árboles. En este proyecto, se prueba la aplicación de un software comercial de sistema de toma de decisiones de IA (Dylogos) a la evaluación de árboles. El software se basa en una nueva lógica dinámica no clásica, que combina diversas fuentes de conocimiento en un sistema emergente para apoyar las evaluaciones de árboles visuales. Un conjunto de reglas describe el conocimiento existente sobre los parámetros en su mayoría poco nítidos que afectan la probabilidad de falla y daño. El software evalúa los datos recopilados durante una evaluación básica del árbol y proporciona una estimación del nivel de riesgo que representa el árbol. El resultado y las razones para ello se presentan en un lenguaje sencillo. Luego, los usuarios pueden examinar esta estimación y alimentar su propia evaluación en el sistema para entrenarlo aún más, de modo que este sistema de IA "blanco" sea de autoaprendizaje basado en la experiencia adquirida en el uso práctico. El uso de la IA en la evaluación de riesgos de árboles no solo apoya al usuario, sino que también se puede utilizar para difundir conocimientos y promover la estandarización de la toma de decisiones en la evaluación de árboles. Las direcciones importantes para futuras brechas de investigación y conocimiento relacionadas con la capacitación de sistemas de IA en ausencia de criterios de riesgo acordados en toda la industria identificados en este proyecto son: cómo recopilar suficientes conjuntos de datos de calidad garantizada para definir el conjunto inicial de reglas; y cómo evaluar el nivel de conocimientos especializados de los usuarios que siguen capacitando al sistema.