Towards decision support system using heterogeneous knowledge and data for assessing new insulating panels from Guyana material

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Context and objective

This research aims to develop an integrated decision support system using heterogeneous knowledge and data to assess the performance of innovative insulating panels made from residual biomass in French Guiana, considering economic, technical, and environmental aspects. this work is part of the PANTHER²Guyane project, which has the goal of creation the use of local biomass residues in producing sustainable and eco-friendly thermal insulation materials, addressing regional challenges such as rapid demographic growth and climate change. The primary challenge in evaluating the performance of these panels lies in understanding and modelling the complex interactions between various components of the manufacturing process across multiple scales in an uncertain environment (e.g., climate change, evolving manufacturing standards, and physicochemical knowledge gaps). Traditional quality control methods, which rely heavily on historical data, often fail to capture the complexities of the process, leading to less accurate predictive models (Zhou et al 2016). This research addresses these limitations by integrating heterogeneous data and expert knowledge. The methodology involves gathering and structuring knowledge from multiple sources, such as scientific literature, internal data, and expert interviews, using concept maps and process maps to create a unified framework (Baudrit et al 2024). This structured knowledge is then used to develop a mathematical model, which is trained and iteratively improved using machine learning algorithms (Bertolini et al 2021). The mathematical model serves as the foundation for decision-making, evaluating the impact of various factors on the insulation panel's performance and predicting future outcomes. The expected outcome is the development of an effective decision support system that helps stakeholders make informed decisions regarding the performance of new created wood panels. This system has the potential to be applied across different industrial sectors, contributing to both economic and environmental sustainability goals.

Methodology

This study follows a systematic and iterative approach to develop a decision support system for assessing the performance of innovative insulating panels made from residual biomass. The methodology is divided into three primary steps: Model Development through Heterogeneous Knowledge, Training the Machine Learning Model, and Performance and Decision Support Evaluation (Fig. 1).

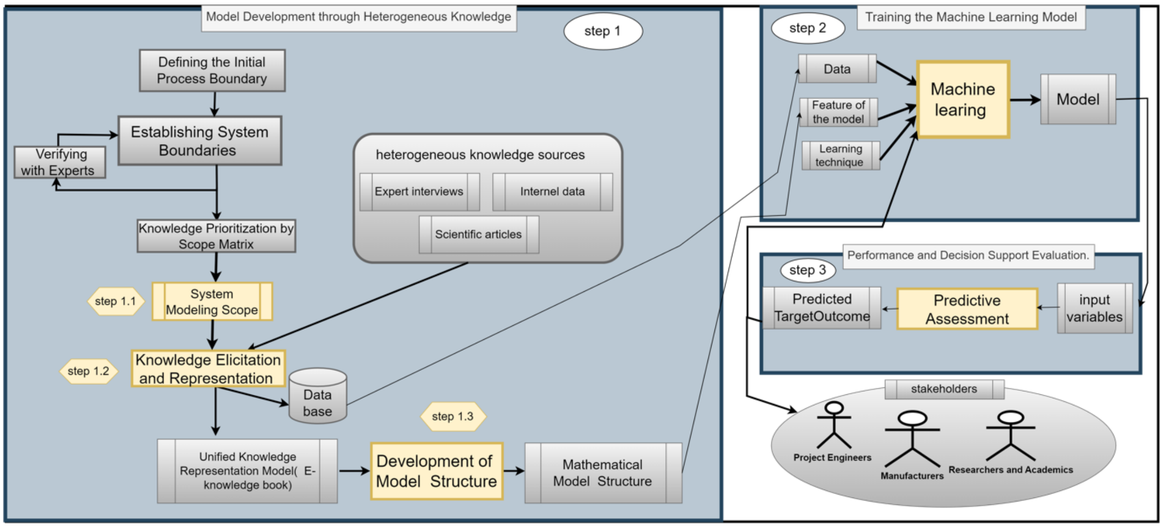

Fig. 1: Overview of the Integrated Methodology for Developing a Decision Support System for Biomass-Based Insulating Panels

Step 1. Model Development through Heterogeneous Knowledge

Step 1.1: System Modeling Scope

The System Modelling Scope is the first sub step to reach. It defines the critical areas of the manufacturing system to be modelled. The first stage of building the scope involves defining the initial global process boundary of the manufacturing system through detailed discussions with the project chief, who has an overarching view of the workflow. This boundary outlines key operational processes and is iteratively refined through unstructured domain-specific expert interviews (Bryman 2001). This iterative validation ensures that the system boundary aligns with real-world operations. Simultaneously an electronic survey was conducted with experts, and their input was integrated using a Scope Matrix (Milton 2007), which is built and employed to prioritize knowledge areas based on their importance and ease of acquisition, helping the project team focus on the most relevant elements for model development. By completing these stages, the System Modelling Scope is finalized as a sharable framework draw, concentrating efforts on the parts of the system most critical for data gathering and modelling.

Step 1.2: Knowledge Elicitation and Representation

The primary objective of this step is to gather and represent both tacit (implicit, experience-based insights) and explicit (clearly defined and documented) knowledge from multiple sources, including scientific articles, internal data, and expert interviews, which are aligned with the processes defined within the System Modelling Scope. By systematically organizing and representing this knowledge, we ensure the development of a Unified Knowledge Representation Model (E-knowledge book), which serves as a formal framework that organizes and defines relationships between the various concepts within the system (Baudrit et al 2024). This structured knowledge and available relevant data are stored in a database, ensuring efficient access, processing, and integration for future mathematical model development. The knowledge gathering process is followed by organizing the collected data into structured formats, such as:

- Process Maps: Defining workflows and variables within the system.
- Concept Maps: Offering a hierarchical view of relationships between concepts.

Step 1.3: Development of Model Structure

The main objective of this step is to construct an initial mathematical model structure by defining key input, control, and output variables. This structure, based on the knowledge organized in the Unified Knowledge Representation Model (E-knowledge book), serves as the foundation for model training and optimization in Step 2 using machine learning techniques.

Steps 2 and 3: Machine learning Training and Decision Support Evaluation

In Step 2, the model is trained using selected input features and target variables based on the structure from Step 1.3. Machine learning techniques are applied to reveal relationships, and iterative refinements improve predictive accuracy. In Step 3, the model performs Predictive Assessment, generating outcomes that help stakeholders assess system performance. Continuous updates with new data further enhance the model's accuracy and reliability.

Decision Support System Overview

The Decision Support System (DSS) in this framework will assist stakeholders like project engineers, manufacturers, and decision-makers in evaluating the performance of biomass-based insulating panels. It will integrate predictive assessment models (step 3), experts knowledge and internal data into a unified system (software). Models, trained via machine learning, provides predictive assessments and actionable insights. The system is continuously refined with new data and feedback to remain adaptive. However, its reliability depends on data quality and expert input, which may limit its accuracy.

Results and Discussion

This section summarizes the results of Step 1: Model Development through Heterogeneous Knowledge, focusing on defining system boundaries, organizing knowledge, and building a mathematical model structure that supports machine learning processes

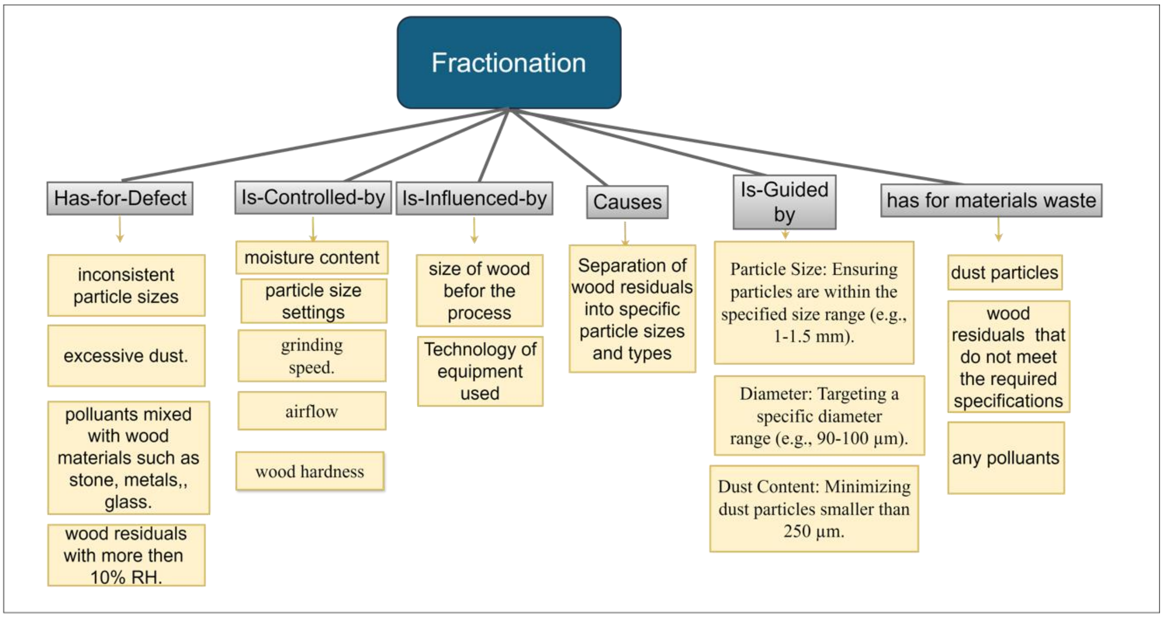

Fig. 2: A Section of the Concept Map for the Fractionation Process in Wood Manufacturing

First work started by defining the system boundary through two interviews with the project chief and two with a key expert. This boundary was refined iteratively through unstructured interviews with domain-specific experts, and additional feedback was gathered via email. Following this, a Scope Matrix was employed to prioritize the most critical knowledge areas, based on a survey with 40% of Panther project expert participation. Processes like fractionation and thermal property studies were highlighted as key for modeling and data collection. To capture both tacit and explicit knowledge, structured and semi-structured interviews were conducted, each lasting around an hour per process. Concept Maps were developed to clarify relationships within the system (Fig. 2), and Process Maps were used to define the key input, control, and output variables, forming the foundation of the mathematical model structure. (Fig. 3)

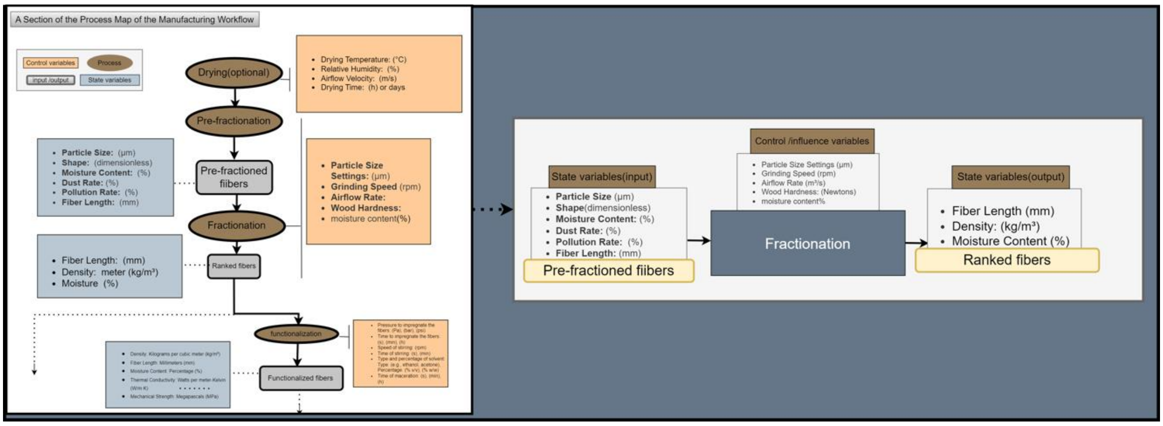

Fig. 3: Developed Fractionation Architecture Model Based on the Output of the Unified Knowledge Representation Model: Process Map

Conclusion and perspective

This preliminary work successfully established the foundational framework for a decision support system to evaluate innovative insulating panels made from residual biomass. By systematically gathering and organizing heterogeneous knowledge, we developed a comprehensive System Modelling Scope and a Unified Knowledge Representation Model, which serve as the basis for the initial mathematical model structure. Moving forward, the focus will be on refining this model through machine learning techniques and predictive assessment. This approach has the potential for broader application across various industries, supporting both sustainable practices and informed decision-making

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