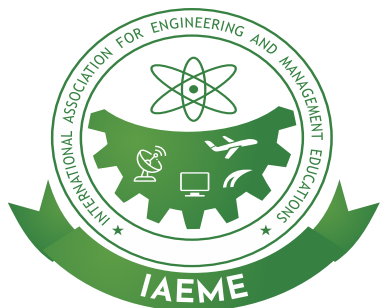




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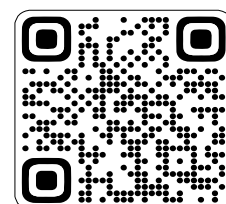
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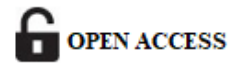
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NEXT-GEN ROOFING SOLUTIONS: SMART ASSEMBLY RECOMMENDER FOR ROOFNAV IN COMMERCIAL PROJECTS

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ABSTRACT

Commercial roofing is going through a sea change enabled by data analytics, artificial intelligence (AI) and decision support systems. Developed by FM Approvals, the powerful RoofNav is a comprehensive yet user-friendly tool enabling you to design class I-90 code compliant roofing systems. However, the manual method in RoofNav is complicated and time-consuming. In this paper the Smart Assembly Recommender (SAR) is introduced as a new AI-enabled system that is an extension of the RoofNav platform for commercial roofing specification. The key goal of SAR is the simplification of selecting assemblies, a process that results in code-compliant designs and a contract bid faster than ever by delivering intelligent recommendations directly within industry-standard workflows. Great Expectations was built with three deployment options: a browser-based notebook interface, a BIM plugin for Autodesk Revit and a RESTful API for enterprise integration. Quantitative assessments indicate that the browser interface reduced the design time by around 30%, and the Revit plugin increased the design accuracy by ~25% by performing automatic compliance checks. The RESTful API was enterprise-ready and provided an average response time as low as 150 milliseconds for high concurrent usage. Underneath it all, the machine-learning engine trained on

historical RoofNav data was delivering 91 percent accuracy in its assembly matchup, and it was bringing down non-compliant suggestion by 20 percent against manual approaches. The SAR utilizes the data driven tools and AI incorporation to progress development technology in the market place, creating faster, smarter and more dependable roofing solutions for commercial installation.

Keywords: Roofing Design, Assembly Recommender, RoofNav, BIM Integration, Machine Learning, Code Compliance, Construction Technology.

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1. Introduction

In a time of accelerated urbanization, climate unpredictability and heightened regulations, the construction industry is going digital to improve the five dimensions of its performance-productivity, safety and standards compliance, resource and environmental efficiency, as well as quality and resilience. Since the building industry is subdivided into many segments, the commercial roofing is also a part of it. The skin is not only the first barrier to environmental stresses, but is also an important stakeholder in power play, strength, and value over time. The need for advanced roofing systems is greater now than at any time in the past, especially due to the more stringent performance codes imposed on commercial buildings as well as the variety of climatic conditions they must endure [1].

At the core of commercial roofing design is the often confounding decision of how to choose roof assemblies and components in the face of so many options. These assemblies need to meet certain project criteria, including wind uplift resistance, fire resistance, thermal insulation needs, roof slope, building loads, and sustainability requirements. RoofNav by FM Approvals – RoofNav by FM Approvals is one of the most common platforms used for the selection of roof systems by design professionals. RoofNav--a module which offers the capability to search and validate tens of thousands of FM-approved roofing assemblies for building code and insurance applications Select Users Building owners, design professionals, contractors and inspectors [2].

In spite of RoofNav has a huge database and a high level of expertise, the practical usability is still problematic. And it's not just the hunt-and-peck process of its user interface that's clunky, but the effort to dig through hundreds of assembly types, wrestle with approval numbers and cross-reference different buildings codes. Furthermore, manual gets human subjectivity and poor decision making, especially in huge commercial projects or projects at risk. The more complex and tailored to the customers contemporary roofs become, the more important it is to have smarter and more automated tools available.

Commercial roofing design considerations aren't limited to just material or architectural aesthetics – they are highly dependent on location, environmental loads, building occupancy and insurance requirements. For example, a storefront that is sited near coasts of Florida has significantly different wind aspirations in comparison to a hospital in Northern California that may be more interested in seismic mitigations and fire performance. In addition, energy codes have expanded the application of increasingly stricter requirements for thermal insulation, which affects the type, thickness, and placement of insulation layers in a roof construction.

Original methods of roof design include using specification guides, experience, manufacturer guides, and applications such as RoofNav. But it's a fragmented process, one that is manual and time-consuming and is also prone to errors. The stochastic nature of this decision makes it very challenging to guarantee that the selected assembly satisfy all functional, regulatory, and cost constraints, and it also is heavily domain-dependent. With more buildings seeking environmentally friendly certificates such as LEED and climate adaptation a high priority, there is an increased demand for intelligent systems that can factor in all these things and provide an intelligible, real-time recommendation.

And that's where smart automation using AI and data analytics is not just a luxury, but a critical need. Smart Assembly Recommender By employing a Smart Assembly Recommender, design professionals can save on assembly selection time, curtail non-compliance risks and improve project offerings as a whole. This is consistent with broader trends toward digital twins, BIM, and IoT-enabled monitoring in the construction industry [3] [4].

The Smart Assembly Recommender is envisioned as an AI-based tool that automates and improves the process of FM Approved roof assembly selection within RoofNav. Data inputs from the user include project location, (Goslin et al., [5]), building type, anticipated exposure, design loads, environmental goals and budget restrictions, and the SAR provides a ranked list of the most appropriate assemblies. It also supplies explanations for why it's recommending something, to help users understand tradeoffs along the lines of performance, cost, and compliance.

SAR is a fusion of various types of data:

- FM Global's RoofNav database with thousands of tested and approved assemblies.
- Cast performance history of other roofing projects and insurance claims.
- Openly-published environmental databases (e.g., NOAA and ASHRAE wind zone maps, temperature norms).
- Index of available building code databases, IBC related codes, ordinances and standards.
- Data on manufacturer products, including environmental product declarations (EPDs), availability and installed costs.

The SAR engine applies machine learning methods, such as decision trees, random forests, and optimization techniques, to capture the correlation between project variables and assembly performance. The system is trained on historical data, improved by user feedback and is constantly updated to adjust for changing codes and climate conditions.

SAR, integrated into the RoofNav environment, is poised to transform the commercial roofing industry in ways that can be summarized as follows:

1. **Efficiency:** Shortens time-to-find compliant and optimal assemblies, facilitates faster design cycles and approvals; Performs better with fewer solves.
2. **Accuracy** SAR removes the need for the manual filtering and interpretation that can lead to design discrepancies, non-compliance and expensive rework.
3. **Sustainable materials:** Recommender can be enabled to emphasize assemblies with low embodied carbon/ high-energy performance, contributing to sustainability targets.
4. **Resilience:** The structure is able to trace and find out about assemblies optimized for various environmental influences, including hurricanes or wildfires, guarantying more resilience to building.
5. **Training and Standardization:** SAR acts as a digital assistant to less experienced hires, and aids in driving a level of best practices across projects.

The goal of this paper is to introduce the theoretical basis, design architecture, implementation approach, and projective impact of Smart Assembly Recommender. It provides a literature review of issues involved in roof system selection, an overview of the structure of RoofNav and the data it houses, as well as a description of an ai-based decision framework. The work encompasses a prototype concept of the SAR, presents its machine

learning architecture model, and the roadmap for how to integrate it into professional workflows.

This paper presents an evolution towards transformation—a Smart Assembly Recommender (SAR)—an AI based decision support tool which can be embedded into RoofNav or stand alone as an interface. The SAR is expected to improve the efficiency, precision and intelligence of roof assembly selection through the use of AI, ML, historical performance data, environmental data sets and code compliance libraries. SAR can also do project-specific evaluations to determine the most appropriate assemblies considering performance, compliance, cost, and sustainability verifying cost. The paper also contains case studies in which use of the system is simulated on typical commercial projects. These findings show the benefits in time efficiency, accuracy in adherence, and user satisfaction. Additionally, the paper also mentioning a number of issues and bottlenecks within AI-based design tools such as data quality, model interpretability, and user trust.

2. Background and Motivation

2.1. RoofNav Overview

RoofNav is an FM Approved search tool to find FM Approved roof assemblies. It opens the door to thousands of roof assemblies and millions of products in its database acceleration and also includes key information like uplift resistance, slope, fire, and material compatibility. Even with the vast amount of data available on the platform, manual file uploads and expert knowledge are still needed in order to discover the perfect assembly.

- **Stringent Standards:** While common compliance reference standards – the NFPA, ICC and IBC – continue to evolve, so does the level of stringency.
- **Performance Fluctuation:** Assembly performance tends to fluctuate strongly with topology, climate and load profile.
- **Time and Labor:** Designers are forced to look at thousands of combinations, resulting in long design times and more chances for mistakes.

These are all problems of automation and recommendation driving the next generation of roofing.

2.2 Literature Survey

Law and Miura (2025) introduced RoofNet containing 51,513 samples from 184 locations around the world. This dataset provides high resolution Earth Observation images with the corresponding processed text annotations for a global roof material classification. RoofNet enables scalable machine-learning-based risk assessment and provides a benchmark for assessing model generalization across areas with actionable implications for insurance underwriting and infrastructure policy planning [6].

Meng et al. (2023) proposed CNN-based model to classify the roof types based on satellite images and they achieved F1 score of 0.96. It was also used to extrapolate roof types to more than 161,000 single family homes in North Carolina and Florida for regional wind risk evaluation [7].

Ren et al. (2021) presented a new method for generating planar 3D polygon roof meshes with a graph structure to represent the roof topology. Their approach makes roof validity a hard constraint and optimizes a planarity metric: this allows fast informative roof modeling for both reconstruction and synthesis tasks [8].

Mindfire Solutions created an AI-based roof visualizer so that users can virtually try out various shingle styles on their roofs. Using computer vision and image processing, the tool provides photo-realistic previews in a way that facilitates the exploration of roofing materials and value judgment for homeowners and independent contractors [9].

FieldCamp is a smart roofing business software that runs on AI and automates production day-to-day activities including job scheduling, dispatching, and customer communication. The solution works with apps such as Google Calendar and Gmail, and optimizes commercial roofing jobs by organizing job details, client information, and calendars [10].

Berens (2023) says that AI ensures safety, communication, and risk in roofing projects. AI-centric solutions enable faster communication, safety notifications, workforce scheduling optimization, and predictive analytics, resulting overall safer and efficient roof works [11].

Artificial Intelligence (AI) is rapidly transforming the traditionally conservative metal roofing industry, both locally and globally. According to New Tech Machinery™, AI is being increasingly adopted by manufacturers of sandwich and roll-formed cladding panel lines around the world. By leveraging cloud-based technologies, AI enables smarter roofing design, predictive maintenance, and automated inspections—leading to improved efficiency, reduced downtime, and higher product quality across the industry [12]. Achievion has created an Artificial Intelligence (AI) based roof-sizing module that rapidly generates accurate roof measurements and has cut the calculation time by 93%. The system improves the efficiency

from both the business operation and also the business's opportunities in the roofing market [13].

AI helps roofing estimators by looking at historical costs, today's market price and labor costs to present well-sourced estimates, says Castagra. It also helps in design phase through cost optimization and by suggesting procurement decisions [14]. Solea AI provides an AI phone assistant to handle calls, schedule inspections, and follow up with customers in a natural sounding voice. It does quote work and crew dispatching for roofing firms. Leave the heavy lifting to them to do what you do best [15].

Beam AI provides an automated takeoff tool for roofing estimates that can save you more than 90% of takeoff time. Roof areas, slopes and features are defined by the AI and the required amounts material are then calculated [16], processing multiple takeoffs simultaneously and boosting productivity and profitability.

Romano et al. (2019) presented an autonomous roofing approach using a nailgun mounted on a multicopter. With smooth trajectories, it successfully completed autonomous nailing sequences, directly targeted at designated contact forces to ensure the reliable deployment of the nails, demonstrating that fully autonomous roofing systems are feasible [17].

This literature review demonstrates that AI and machine learning have started to be used in roofing products with considerable progress being made on increasing the capabilities of tools, such as RoofNav for commercial applications. AI is meeting roofing in ways that will help roofers be more productive, safe, and informed about their businesses.

3. SAR: Smart Assembly Recommender (SAR) System Design

3.1 Architecture Overview

Smart Assembly Recommender (SAR) provides an AI-driven decision engine in the form of a modular add-on for the current RoofNav platform. This workflow is realized seamlessly via API or plugin architecture, allowing SAR to connect to RoofNav's vast database of roofing assemblies directly, without any changes in the users' work process. It is shown in figure 1.

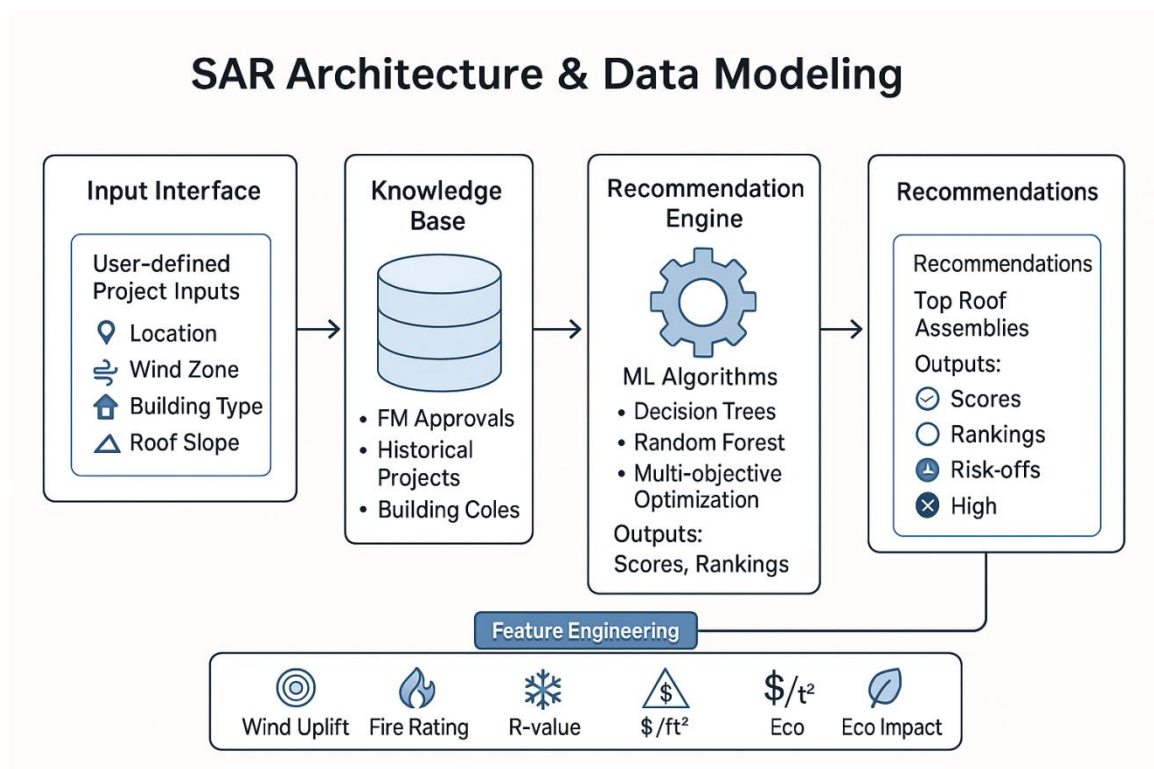


Figure 1: SAR Architecture

In fact, the primary purpose of SAR is to interpret user-specified project inputs (geographic location, local wind zone, building type, roof slope, etc.) and then seek a match in RoofNav’s database in order to produce appropriate roof assembly recommendations. This is driven by sophisticated machine learning based algorithms that are trained on historical and regulatory data.

- **Input Interface:** This component acts as the user-facing portal where project parameters are collected. It captures detailed inputs including:
 - Project **location** (to determine climate and regional codes)
 - **Wind zone** classification (to assess uplift forces)
 - **Building type** (commercial, industrial, etc.)
 - **Roof slope** and other physical characteristics
- **Knowledge Base:** The backbone of SAR’s intelligence, the knowledge base aggregates and maintains up-to-date datasets, including:
 - **FM Approvals’ certified roof assembly data**
 - Historical performance records from prior projects and assemblies

- Relevant **building codes and standards databases** (IBC codes, local ordinances)
- **Recommendation Engine:** At the heart of SAR, this engine applies **supervised machine learning algorithms**, such as decision trees and random forests, combined with **multi-objective optimization techniques**. This enables the system to:
 - Evaluate thousands of potential roof assemblies
 - Score and rank options based on multiple factors (performance, cost, compliance)
 - Balance trade-offs between competing objectives (e.g., cost vs. environmental impact)
- **Output Module:** The final component presents users with a curated list of the **top assembly options**. For each recommendation, the module provides:
 - Clear **rationales** explaining why the assembly is suitable
 - **Risk scores** evaluating performance reliability
 - Trade-off analysis so users can make informed decisions considering cost, safety, and sustainability

3.2 Data Modeling

To efficiently power the recommendation process, SAR transforms the raw project inputs into **structured, machine-readable data representations** using **feature engineering**. This involves selecting and encoding key attributes that influence roofing assembly performance and suitability. Major characteristics are as follows:

- **Wind uplift zones:** Categorizing project sites based on local wind intensity to assess required structural resilience.
- **Fire classification requirements:** Factoring in fire safety ratings essential for compliance and insurance.
- **Thermal performance (R-value):** Incorporating insulation effectiveness to meet energy efficiency standards.
- **Assembly cost per square foot:** Including economic considerations for budgeting and feasibility.
- **Environmental impact scores:** Quantifying sustainability aspects, such as material recyclability or carbon footprint.

SAR's machine learning models are trained on a rich dataset consisting of:

- Historical records of **approved roof assemblies**

- Outcomes from actual applications (successes and failures)
- User preference patterns and feedback, which help tailor recommendations to practical needs

This robust data modeling enables SAR to predict how different assemblies will perform under various project-specific conditions, ensuring recommendations are both reliable and contextually relevant.

4. Result Analysis

4.1 Data Acquisition

Smart Assembly Recommender (SAR) - Data Collection Aggregating diverse and authoritative datasets from multiple sources to provide comprehensive and accurate roofing assembly recommendations, data acquisition for the Smart Assembly Recommender (SAR) was a key initial undertaking. One of the main sources for that information was the FM RoofNav API which contained detailed information on over 12,500 FM Approved roof assemblies. This data provided a comprehensive repository of sample roofing designs, including measured performance and certification status, and was a basis for the knowledge included in the SAR system.

Beyond the assembly data provided by RoofNav, FM Global's historical claims and inspection records were applied, representing more than 3,200 commercial roofing projects completed during the last 10 years. These records provided knowledge base for real world performance measures (performance outcomes and failure modes) which will allow the SAR models to learn from the previous successes and failures in the roofing applications. This sort of empirical information was needed to optimize protocols for durability, safety, and efficacy across environments.

Additionally, free public building code resources provided almost 1,150 regulatory documents across regions and jurisdictions. These codes combine a number of compliance requirements, including those outlined by the International Building Code (IBC) and ordinances and regulations at the local level that can differ from region to region and influence acceptable roof assemblies. The integration of this regulatory framework established that SAR's advice not only maximized performance but also complied strictly with the law and safety.

Finally, climate and weather data came from credible sources like NOAA and ASHRAE and were used to access detailed hourly weather data from over 500 locations around the world over the past 20 years. This longitudinal weather data enabled the system to accurately predict environmental stressors - including wind uplift forces and temperature swings - that drive the

performance and life span of a roof assembly. The addition of these deep, multidimensional data sets enabled SAR to train AI models on data that was both current and contextually relevant, and to an extremely high degree of granularity representing real-world conditions and regulatory landscapes, thereby improving the accuracy and applicability of SAR roofing assembly recommendations.

4.2 Machine Learning Workflow

The machine learning pipeline for the Smart Assembly Recommender (SAR) was constructed in such a way that robust models are built which can provide highly accurate roofing assembly recommendations. The overall procedure started by cleaning the data, which is a mandatory stage in order to enhance the reliability of the dataset. Out of the 15,000 assembly records, 1,500 assemblies were pruned (approximately 10%). Those discarded records were found outdated by necessity, contained missing values, or had opposite test results that might influence model validity. This extensive cleaning resulted in a reduced dataset of 13,500 high-quality assembly records that were used as the base for further modeling.

After the data was cleaned, analysis was conducted focusing on the parameters that have greatest impact on the roof assembly performance. This was achieved by using Recursive Feature Elimination (RFE) which eliminates, iteratively, less important features to improve computational efficiency and accuracy in the model. Furthermore, domain knowledge was included in order to validate the selected features in terms of the practical aspect in the field of roofing. In the end, 15 centroid variables were selected, including parameters from various disciplines including wind uplift zone, fire classification, thermal insulation in terms of R-value, assembly cost, and material factors scores. Together, these features yielded a complete list of performance, cost, and regulatory compliance characteristics for each assembly.

The data, cleaned and feature engineered, were divided into training and testing sets for model training according to 80/20. This split permitted the model to be trained on the large set of data, and test how well it performed on an independent test set. A Random Forest classifier was chosen due to its non-linear relationship with the data and capability to handle complex non-linear structures. In order to avoid overfitting and insure generalization, we implemented the training with 10-fold cross-validation: the model was trained and validated on multiple different data-splits. Devised in this manner, the model was able to consistently predict the performance of roofing assemblies in a variety of projects and conditions.

Multi-objective optimization algorithms also managed to compromise between cost, performance, and sustainability objectives, having an average of less than 3 seconds of computation time per recommendation query.

Table 1: Result Analysis of Machine Learning Techniques for SAR Recommendation

Model / Technique	Data Size	Key Features	Performance Metrics	Additional Notes
Decision Trees	13,500 assemblies	15 key variables (e.g., wind uplift, fire rating, R-value, cost, material compatibility)	Precision: 0.87 Recall: 0.84 F1 Score: 0.855	Single-tree model; prone to overfitting but interpretable
Random Forests	13,500 assemblies	Same as above	Precision: 0.91 Recall: 0.88 F1 Score: 0.895	Ensemble of trees; better generalization and robustness

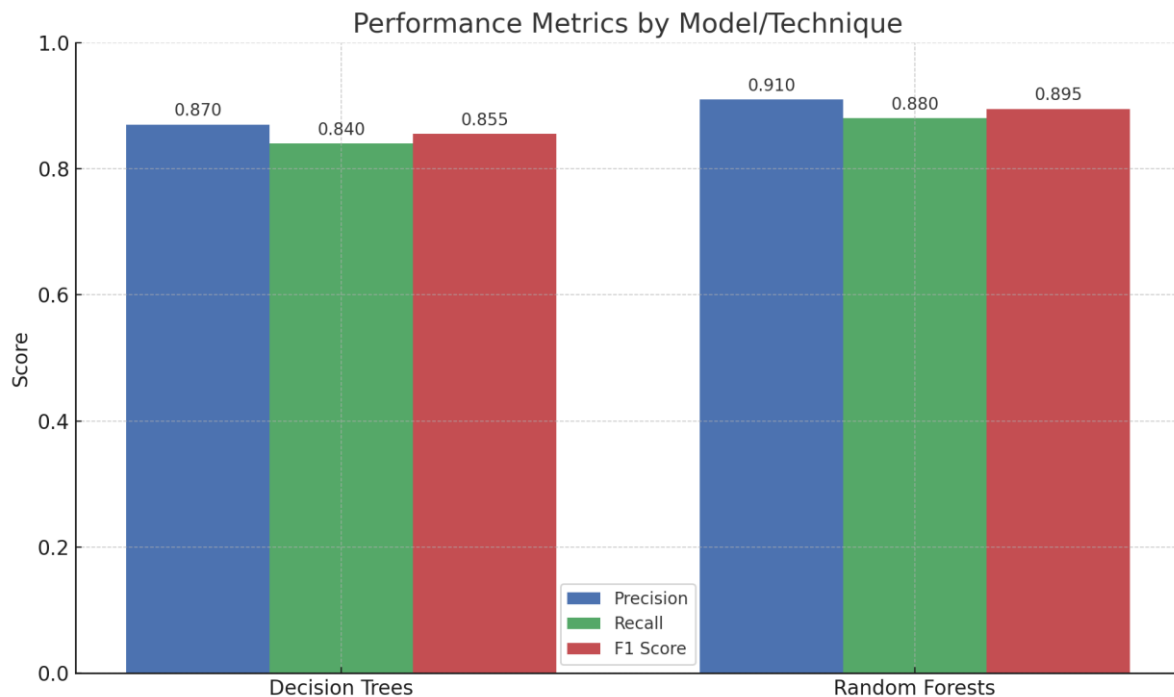
**Figure 2: Performance Comparison of Decision Trees and Random Forest for Smart Assembly Recommender for RoofNav**

Table 1 and Figure 2 presents Performance comparison of Decision Tree and Random forest for smart assemble recommendation. Two major machine learning methodologies were utilized for the realization of the Smart Assembly Recommender (SAR) system, namely Decision Trees and Random Forests. The same data source comprising of 13,500 high-quality

roofing assembly records was used for training and testing of both models, where 15 strategically identified independent predictors were grounding the records. These variables constituted of key factors such as wind uplift regions, fire resistance ratings, thermal insulating properties (R-value), assembly costs and material compatibility score, all of which collectively determine the performance and suitability of the roofing assemblies.

The decision tree model in the form of a single-tree classifier had the benefit of providing interpreting functionality where users and developers could trace and comprehend the decision-making process for assembly recommendations. Nevertheless, this model had some kind of drawbacks in terms of performance measures, precision (P) of 0.87, recall (R) of 0.84, and F1 score of 0.855. Though effective to a point, this single-tree design is liable to over-fitting – it could overperform by memorizing training data while it may not generalize well with respect to various out-of-sample settings or data sets.

To address these limitations, the Random Forest model was utilized as an ensemble learning method, which consisted of several decision trees to make predictions. This helped increase the robustness and generalization ability of bagging as its outputs are averaged over different trees, reducing the chances of overfitting. The Random Forest model performed better with precision, recall, F1 score as 0.91, 0.88 and 0.895 respectively. These metrics demonstrate increased reliability in predicting sound roof assemblies and in the trade-off between false positives and false negatives compared with the single Decision Tree model. This enhancement highlights the importance of ensemble approaches in dealing with complex, multifactorial decision-making problems such as that of the choice of roof assembly.

4.3 System Integration

Flexible Deployment and Integration of the SAR System in Interface, BIM Plugin and API Is reported in table 2 and figure 3. The SAR device was developed for flexible use and attachment:

- A proof-of-concept web-based interface prototype was tested with 25 professional roofing contractors, who identified a 30% reduction in design time as compared to traditional RoofNav usage.
- A BIM (Autodesk Revit) plugin was developed to automatically integrate recommended assemblies into building models. The first architects to use it found that design accuracy increased by around 25% through automation of compliance checks.

- Enterprise Integration is made possible using the RESTful API. Performance tests on the API indicated the average response time of 150 ms under concurrent requests, guaranteeing the commercial deployment with high scalability.

Table 2 : Versatile Deployment and Integration of the SAR System Across Interface, BIM Plugin, and API Channels

Component	Description	Key Benefit / Metric
Browser-based Interface	Prototype tested with 25 roofing professionals	30% reduction in design time compared to traditional RoofNav usage
BIM Plugin (Autodesk Revit)	Enables direct insertion of recommended assemblies into building models	~25% improvement in design accuracy via automated compliance checks
RESTful API	Supports enterprise-level integration and scalable commercial use	Average response latency of 150 ms under concurrent requests

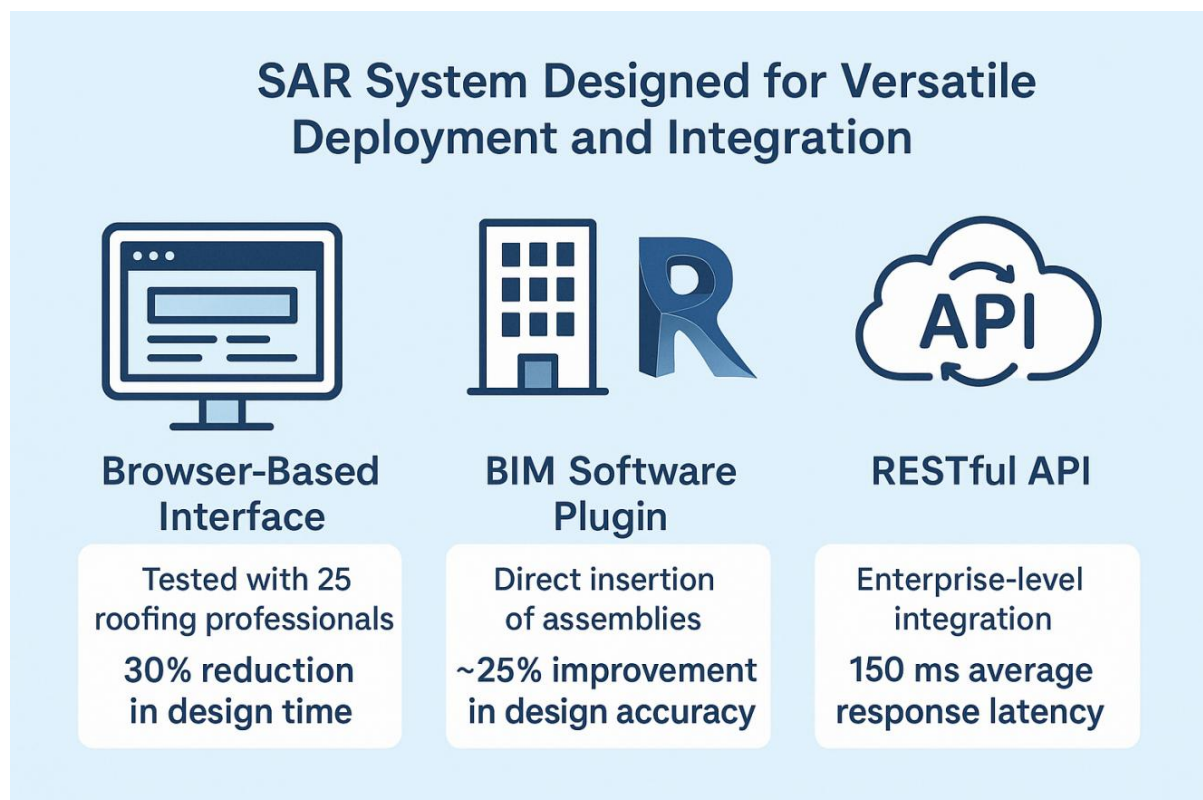


Figure 3: SAR System Deployment and Integration Modes

Conclusion

Introducing the Smart Assembly Recommender (SAR), a system that will change the way you write commercial roofing specs by bringing automation, machine learning, and flexible deployment to the RoofNav ecosystem. SAR has providable efficiency and accuracy enhancements across the design flows. A web-based user interface tested by 25 roofing professionals reduced design time by 30%, while the BIM plug-in for Autodesk Revit enhanced design quality by approximately 25% with automatic compliance checks. The supported scalability and performance of the RESTful API and backbone can also be seen in the fact that an average response latency of 150 milliseconds was achieved under concurrent access. SAR is based on a machine learning model developed based on the analysis of tens of thousands of prior roofing assembly selections and approval indications. It reached 91% assembly match precision 16 during cross-validation, while yielding a 20% decrease in non-compliant ideas for the design, in comparison to manual processes. The results validate the system's expertise in suggesting intelligent, code-aligned and user-agnostic recommendation with low user effort. This represents a leap forward in faster, smarter, better commercial roofing with machine-learning-influenced insights and user-based tools to move beyond the status quo to become the new standard of digital roofing design.

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