Periodica Polytechnica Civil Engineering


# An Agentic AI Framework for Sectional Analysis of Reinforced Concrete Columns when Subjected to Fire


Viet-Tam Tran[1], Truong-Thang Nguyen[1*], Tuan-Ninh Nguyen[1], Viet-Hung Dang[1]

[1] Faculty of Building and Industrial Construction, Hanoi University of Civil Engineering (HUCE), No.55 Giai Phong Rd., Bach Mai Wd., Hanoi, Vietnam

[*] Corresponding author, e-mail: thangnt2@huce.edu.vn



Received: 18 April 2026, Accepted: 06 July 2026, Published online: 27 July 2026



**Abstract**

This paper presents an agentic AI framework that automates the multi-stage analysis process for evaluating the load-bearing capacity of reinforced concrete columns under fire conditions through natural language interaction. First, a large language model orchestrator, equipped with a formal ontology for reinforced concrete structures based on international design codes, interacts with the user. The ReAct technique and LangChain framework are then utilized to decompose user requests into sub-tasks for a series of specialized agents: a data ingestion agent; a thermal analysis agent integrated with ANSYS for heat transfer simulations under ISO 834 standard fire exposure; and a structural capacity and visualization agent, named CFire, which computes residual axial capacities and plots axial force-biaxial bending moment interaction diagrams based on temperature-dependent stress-strain relationship theory. Furthermore, the retrieval-augmented generation paradigm equips the agentic system with expert domain knowledge. The applicability of the proposed agentic system is demonstrated via different reinforced concrete columns, showing that it automates repetitive and tedious tasks in structural fire engineering, such as the manual translation of geometric, material, and temperature data into heat-transfer models and code-compliant load-bearing calculations, thereby significantly improving productivity across the entire analysis process.



**Keywords**

agentic AI, large language model, retrieval augmented generation, reinforced concrete, column, sectional analysis, fire


## 1 Introduction

Reinforced concrete (RC) columns serve as fundamental load-bearing components; consequently, evaluating their structural integrity under fire conditions is critical for ensuring the safety of buildings and infrastructure. The inherent passive fire resistance of RC columns is afforded by the concrete cover encasing the steel reinforcement. When subjected to fire, however, the mechanical properties of both concrete and reinforcing steel deteriorate progressively as temperatures rise. This degradation leads to a gradual reduction in load-bearing capacity that can critically endanger the stability of the entire structural system. To gain a deeper understanding of the complex behavior of RC columns under fire-including temperature distributions, the interaction between axial forces and bending moments, and residual strengths-researchers must conduct multi-stage structural analyses spanning thermal simulation, temperature-dependent material characterization, and cross-sectional capacity assessment. Furthermore, iterative design modifications are required to satisfy fire resistance requirements and safety criteria. Numerous studies have investigated the fire behavior of RC columns, given the complexities arising from material degradation, geometric configurations, and fire exposure conditions.

A fairly large number of analytical and numerical works have been developed to study the structural behaviour of RC columns under fire conditions with respect to thermal and structural analyses. Lie et. al [1, 2] respectively developed similar mathematical models for circular and rectangular RC columns subjected to fire to predict temperature distribution, deformations, and strength of the columns. Finite difference method was used for calculating column temperatures and a sectional analysis was utilised to derive the strength of columns at incremental time steps. A simplified calculation method for the design of RC columns under fire conditions was developed by Dotreppe et al. [3], based on their test data [4] as well as those reported in the literature [5, 6]. The calculation procedure has been simplified by using the proposed reduction factors, based


**Cite this article as:** Tran, V.-T., Nguyen, T.-T., Nguyen, T.-N., Dang, V.-H. "An Agentic AI Framework for Sectional Analysis of Reinforced Concrete Columns when Subjected to Fire", Periodica Polytechnica Civil Engineering, 2026. https://doi.org/10.3311/PPci.44369

on a formulation initially developed for steel columns. Tang [7] extended the Rankine method, in which failure load is determined from plastic collapse and elastic critical loads by using an empirical equation, to the fire resistance prediction of RC columns. Kodur et al. [8] introduced a numerical model for predicting the behaviour of high performance concrete columns exposed to standard fire exposures, which consisted of three steps of calculation: (i) Determination of temperature of fire exposure; (ii) Determination of temperature profile within the column; and (iii) Calculation of column deformation and strength. In their study, Tan and Yao [9] developed a simple and rational method to predict the fire resistance of RC columns subjected to four-face heating based on the ACI method at ambient temperature.

The approach comprised the determination of the respective strength reduction factors of concrete, reinforcement steel, and elastic modulus at elevated temperature on the basis of numerical simulations using the computer program SAFIR. Bratina et al. [10] proposed a numerical model for tracing the behaviour of RC columns under fire conditions. A two-step finite element formulation for the thermo-mechanical non-linear analysis of the behaviour of RC columns in fire was developed, in which the determination of temperature distributions in the cross-section during the heat transfer process and mechanical analysis were conducted. Transient strain was incorporated into the concrete model in this study. Kodur and Raut [11] proposed a simplified approach for predicting fire resistance of RC columns under biaxial bending accounting for the effects of fire-induced spalling, 1-, 2-, 3-, or 4-side fire exposure, bi-eccentric loading and design fire scenarios through a large number of numerical studies. Barmonte et al. [12] compared the effect of different constitutive models for concrete at high temperature on the strength of reinforced concrete columns exposed to standard fire. A Finite Element code aimed at the thermo-mechanical analysis of reinforced concrete members in fire is introduced, in which four different constitutive models for concrete compressive behaviour in hot conditions were considered. The results obtained are capable of highlighting the differences between explicit and implicit formulations of the stress–strain relationship.

Most of the analytical methods reviewed used the simplification of dividing the interaction between structures and fire exposure into three distinct consecutive steps: (i) Determination of the changing temperature with time; (ii) Determination of the temperature in the concrete by heat transfer; and (iii) Determination of the time-dependent mechanical response of columns based on combined mechanical and temperature loads. Nguyen et al. [13] introduced a rigorous cross-sectional analysis based on inclined neutral axes, a proposed limit of failure strain, and specifications for thermal and mechanical properties in accordance with EC2 Pt.1.2 [14] to determine the temperature-dependent axial and moment resistances of an RC column. Failure times of the heated columns can be evaluated based on a number of proposed failure modes. This rational approach was verified using the test data obtained from [15, 16] as well as a fairly large number of fire tests collected from other laboratories [17].

The integration of Large Language Models and automated computational frameworks is currently reshaping civil engineering, transitioning the field from manual workflows to smart systems. AI-integrated frameworks have been successfully applied to different subfields such as creating fast surrogate models for significantly reducing computational time [18, 19]. Other advancements include the combination of Building Information Modeling (BIM) and visual programming to guide Finite Element Method (FEM) frameworks within automated design-to-fabrication workflows [20]. Sebastian et al. [21] introduced an automation framework for structural analysis that uses speech recognition to process voice commands for defining structural elements and loads. The authors reported that this voice-driven interaction can reduce analysis time by approximately 30%. Nguyen et al. [22] applied prompt engineering to integrate domain knowledge of vibration signals with LLM for structural damage detection, enabling users to build reliable monitoring applications without requiring advanced programming skills or specialized software. For construction quality management, a framework utilizing BIM, and natural language processing was proposed to help consolidate scattered project knowledge [23]. To automate rule checking, the LLMFuncMapper framework was developed to translate regulatory clauses into executable code through a library of functions [24], capturing the complex requirements necessary to verify design solutions against regulations.

Hope et al. [25] assessed LLM performance and found that, while LLMs can outperform many engineering students, they still struggle with interpreting visual diagrams and solving real truss structure problems, highlighting the need for enhanced multimodal capabilities in engineering AI. Recently, the advancement of agentic AI has led to a transformative shift in AI engineering applications, from passive models into autonomous systems that can perform proactive planning, contextual memory, and flexible adaptation to environmental changes [26]. In construction management, the workflow introduced by Li et al. [27], parses project documents into hierarchical knowledge and applies novel search and voting algorithms to tailor results to specific user roles, which significantly improves communication. Similarly, BuildingGPT employs a vector-graph retrieval-augmented generation pipeline to bridge the gap between complex semantic building data and natural language queries [28]. The integration of deterministic computational models is standardized by the Model context protocol (MCP), which provides a context-aware interface for general interaction between AI systems and domain-specific software [29]. Based on MCP, the EnergyPlus-MCP server by Li et al. [30] implements 35 specialized tools for building energy modeling, successfully bridging sophisticated simulations to natural language interfaces.

Given the significant potential of agentic AI, this study introduces an agentic system for evaluating the load-bearing capacity of reinforced concrete columns under fire through natural language interaction, named CFA (Agentic system for reinforced concrete Column under Fire). The proposed system is capable of autonomously conducting thermal analysis under standard fire scenarios, constructing axial force–moment interaction diagrams at elevated temperatures, and auditing compliance with fire design provisions. The system not only serves query-answering purposes or automates individual analysis steps, but spans the entire fire resistance assessment cycle, from column geometry definition and thermal modeling, to structural capacity evaluation, code compliance checking, and interactive visualization. The framework's main components consist of a large language model orchestrator equipped with a formal ontology for RC structures, a data ingestion agent for parsing geometric and material inputs, a thermal analysis agent integrated with ANSYS for heat transfer simulations under ISO 834 standard fire exposure [31], an analysis agent named CFire for computing residual capacities and plotting interaction diagrams, and a retrieval-augmented generation component that extracts fire design requirements from international standards, such as Eurocode 2.

In the remainder of this paper, Section 2 describes the overall workflow and key components of the proposed CFA agentic system. Section 3 demonstrates the applicability and credibility of the proposed system through various RC column case studies. Finally, Section 4 draws conclusions and suggests potential directions for future research.

## 2 Methodology

The overall workflow of the agentic system for reinforced concrete column fire analysis is graphically presented in Fig. 1. This agentic system consists of the following components: a large language model-based orchestrator; a

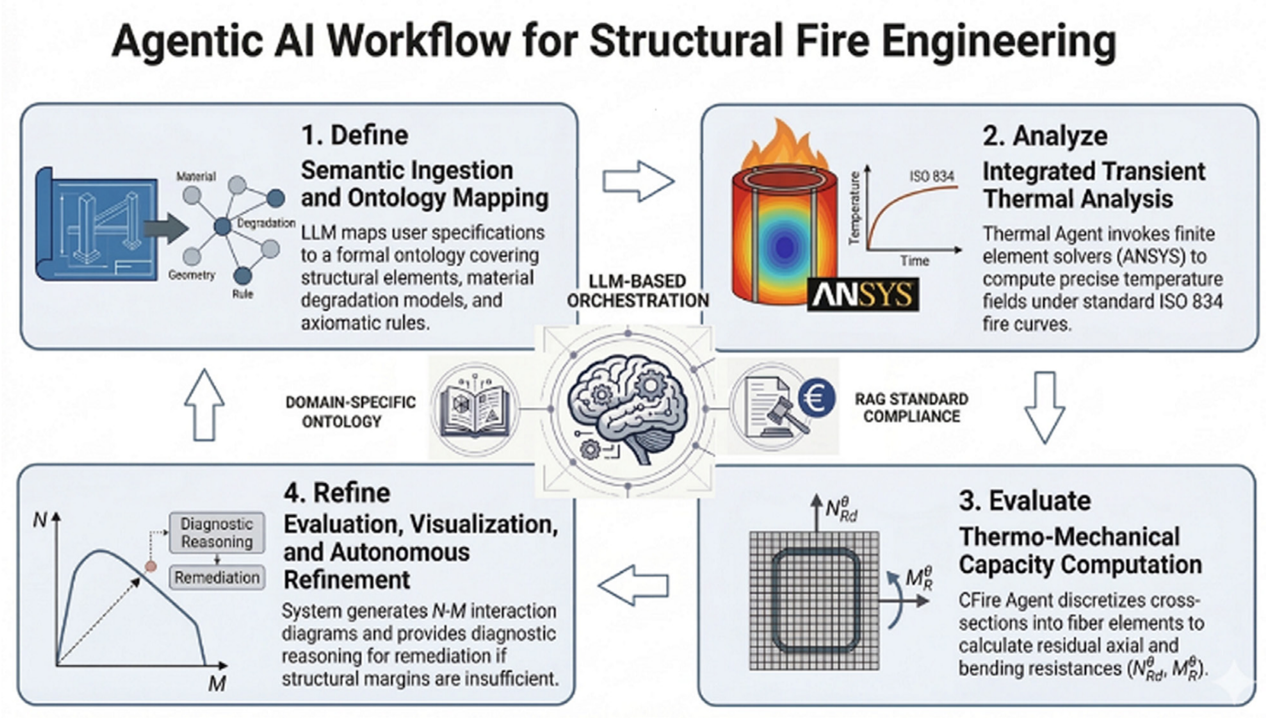



**Fig. 1** Overall workflow of the agentic AI system for reinforced concrete columns in fire

formal domain-specific ontology derived from EN 1992-1-2, ISO 834, and related scientific literature; a thermal agent that invokes finite element solvers to compute two-dimensional temperature fields within the column cross-section; a structural fire engineering computation module that calculates the residual load-bearing capacity; and a desktop graphical user interface with visualisation. These components are seamlessly integrated into a unified conversational workflow that facilitates interaction between the user and the agentic system via a chatbot interface. The user can instruct the LLM agent using natural language commands to perform tasks such as "Define a 300 × 400 mm column, C35/45, $N_{\mathrm{Ed}}$ = 2000 kN" or "Run the fire analysis for 120 minutes", after which the system invokes the corresponding computational tools. In addition, quick-action buttons are provided in the sidebar of the graphical user interface to directly trigger the analysis sequences. Furthermore, to designate the LLM-based orchestrator as a specialist in structural fire analysis, a system prompt is configured as illustrated in Fig. 2.

### 2.1 Ontology development for an agentic AI system in reinforced concrete column structural fire engineering

To facilitate reasoning and semantic interoperability within a multi-agent Large Language Model framework, a formal ontology is established to capture the geometric, thermo-mechanical, and analytical characteristics of reinforced concrete columns under fire conditions. This ontology serves as the foundational knowledge base for the CFA agents, allowing them to orchestrate the design–analyze–evaluate cycle based on the specifications in Eurocode EN 1992-1-2 [14]. The ontology architecture is hierarchically divided into three high-level branches to support agentic reasoning: structural element, material in fire, and analytical model. The first branch defines the column configuration, including width, depth, rebar diameter, number of rebars, and concrete cover. Furthermore, the external environment is described by the ISO 834 standard fire curve, and the boundaries are parameterized as exposure conditions, such as four-sided fire exposure. The ISO 834 curve is expressed as follows:

$$T = 20 + 345 \log_{10}\left(8t + 1\right) \tag{1}$$

where $T$ is temperature in °C and $t$ is time in minutes.

The second branch of the ontology provides the theoretical background for temperature-dependent degradation. Concrete inherently possesses low thermal conductivity and high heat capacity. However, as fire exposure continues, its properties alter through several mechanisms: concrete spalling, degradation of compressive strength, tensile strength and modulus of elasticity. By 600 °C, concrete can lose about 55% of its ambient strength. In addition, the total deformation of concrete ($\varepsilon_{tot}$) in fire is governed by four distinct strain components: thermal strain ($\varepsilon_{th}$), stress-related strain ($\varepsilon_{\sigma}$), creep strain ($\varepsilon_{cr}$), and transient strain ($\varepsilon_{tr}$) as follows:

$$\begin{aligned}\varepsilon_{tot}\left(T\right) &= \varepsilon_{th}\left(T\right) + \varepsilon_{\sigma}\left(\sigma, T\right) + \varepsilon_{tr}\left(\sigma_h, \sigma, T\right) \\ &+ \varepsilon_{cr}\left(t, T, \sigma\right)\end{aligned} \tag{2}$$

Conversely, steel is a highly thermally conductive material. Although it can maintain its mechanical properties up to 100–200 °C, its properties change drastically when subjected to temperatures above 600 °C. For example, as specified in Eurocode 2, it may retain less than 50% of its maximum yield stress, 20% of its proportional limit, and 30% of its tangent modulus of elasticity. Moreover, as temperatures rise, steel undergoes significant thermal expansion while concrete is subjected to compressive contraction. These materials deform differently, leading to increased thermal stresses that break the bond between them, thereby further degrading the load-bearing capacity of the column.

Finally, the analytical branch dictates the mathematical derivation of the column's load-bearing capacity. It is assumed that the cross-section remains plane after

```
SYSTEM_PROMPT = """You are the Structural Fire Engineering Agent orchestrating a 4-step load-bearing analysis workflow for RC columns under fire exposure.

CAPABILITIES
--------------------------------------------------------------------
1. DATA INGESTION   [read_user_input_form]
  Reads structured structural parameters provided via the user input form. Variables include column width (b), depth (h), concrete compressive strength grade, reinforcing steel layout, and concrete cover.

2. THERMAL ANALYSIS INTEGRATION   [run_ansys_thermal_analysis]
  Transmits user geometry and material data to ANSYS. Executes a transient thermal analysis under standard fire conditions. Commands ANSYS to calculate and export the precise temperature distribution data across the column's cross-section at requested time increments.

3. EUROCODE CAPACITY COMPUTATION   [calculate_eurocode_capacity]
  Ingests the user's structural data alongside the spatial temperature fields exported from ANSYS. Applies temperature-dependent material reduction factors and cross-sectional equilibrium equations strictly according to Eurocode (EN 1992-1-2) to compute the degraded load-bearing capacity.

4. VISUALIZATION & REPORTING   [plot_interaction_diagram]
  Processes the computed capacity data to generate and display the N-M interaction diagram (axial force vs. bending moment) for the RC column at any user-specified fire exposure time (e.g., t = 60 mins, 90 mins, 120 mins).

GUIDELINES
  - Execute the workflow strictly in sequence: Form Data -> ANSYS Thermal -> EC Calculation -> Interaction Diagram.
  - Verify that the spatial mesh coordinates from the ANSYS temperature export align perfectly with the fiber discretization used in the Eurocode capacity calculation.
  - Confirm each operation with a brief numerical summary (e.g., "ANSYS thermal data successfully extracted for t = 90 mins with maximum temperature of 850°C").
  - Always explicitly cite the specific EN 1992-1-2 clauses utilized during the capacity calculation step.
  - If ANSYS fails to converge or export data, state the error clearly and suggest a mesh refinement or time-step adjustment.

WORKFLOWS
  Standard Fire Analysis: Ingest Form Data -> Run ANSYS Thermal -> Compute EC Capacity -> Plot Interaction Diagram
```

**Fig. 2** System prompt for the fire-agentic system bending and normal to the centroidal axis. When the total strains in the reinforcing bars and their adjacent concrete fibers still are equal, it can compute stresses in concrete and steel elements directly from mechanical strains using the corresponding temperature-dependent non-linear stress-strain curves. A structural failure state occurs when the maximum mechanical compressive strain in the concrete reaches defined ultimate limits, e.g., the strain limit $\Delta\varepsilon = 1 \times 10^{13}$ mm/mm for EN 1992-1-2 applications. On the other hand, the tensile strength of concrete at elevated temperatures and shear deformation effects are deliberately negligible in the analysis. A neutral axis defined by a distance from the extreme compressive concrete fiber $c_n$ and an inclined angle $\beta$. As heat penetrates the column from the exterior, the temperature distribution is non-uniform across the section, the compression zone becomes irregular and deviates from a standard rectangular block. The analytical process begins by discretizing the cross-section into a 2D grid of small rectangular elements and steel rebars. For a specific neutral axis characterized by ($c_n$, $\beta$), the temperature, strain, and stress of each discrete rectangle are calculated. These values are integrated across the entire section to determine the corresponding axial force and the two bending moment resistances. By varying $c_n$ and $\beta$, one obtains the $N$-$M_y$-$M_z$ interaction surfaces for a given fire exposure duration.

### 2.2 Large language model-based orchestration

The traditional computational workflow in structural fire engineering has been carried out by deterministic, static pipelines. The thermal and mechanical assessment of reinforced concrete columns under fire requires manual translation of geometric and material data into heat-transfer models and code-compliant load-bearing capacity calculations. Numerical outputs, such as cross-section temperature distributions and residual axial capacities, are subsequently interpreted by experts to revise the design solutions. While scripting interfaces have introduced a degree of automation to these workflows, such implementations remain fundamentally hard-coded and lack semantic understanding. The emergence of Large Language Model (LLM)-based orchestration represents a paradigm shift, supplanting static pipelines with conversational, adaptive processes that respond dynamically to user intent. In this framework, the DeepSeek-Chat model [32] is utilized, it receives natural language specifications and maps them to the corresponding modules. Rather than executing a predetermined sequence of operations, the LLM transforms the fire engineering workflow into an interactive, context-aware process (Fig. 3). Specifically, the ReAct (Reasoning + Acting) paradigm [33] is employed. This framework, the LLM receives a natural language request, reasons about which domain-specific tool to invoke, executes that tool, observes the returned result, and subsequently synthesises human-readable responses.

For this purpose, the LangChain [34], an open-source framework, is employed for constructing LLM-powered applications. LangChain abstracts language models as interchangeable backends via the BaseChatModel interface, treats tools as callable functions, and represents

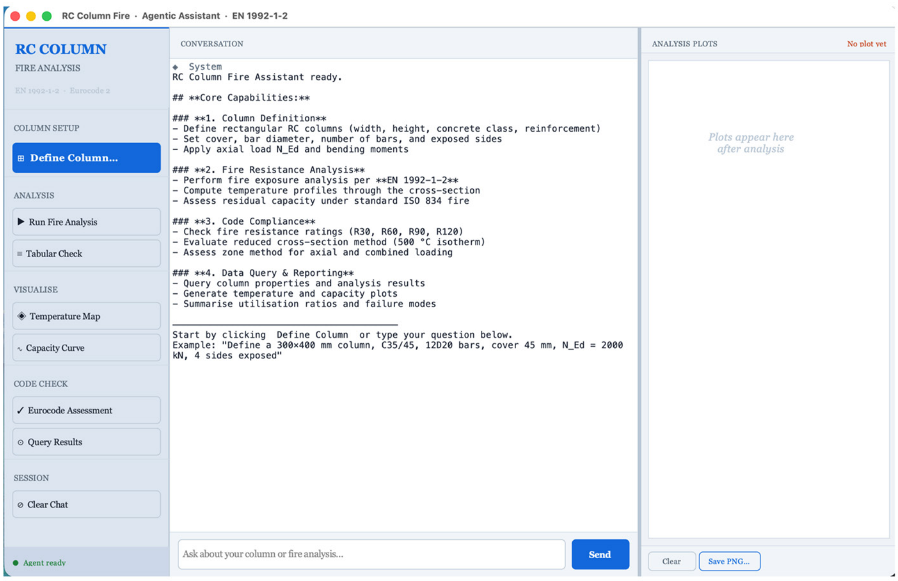



**Fig. 3** Graphic user interface of CFA featuring quick-access commands at the sidebar, a central chat window for natural language interaction and prompts, and a visualization panel

workflows as sequential or graph-based chains. Its core architectural components comprise: (i) chains, which define linear sequences of LLM calls; (ii) agents, which leverage LLMs to select and invoke tools; and (iii) memory modules, which maintain conversation history to prevent context loss across multi-turn interactions. Within the ReAct loop, the model interleaves explicit reasoning traces (Thoughts) with executable actions (Tool Calls) and environmental feedback (Observations). Upon receiving a natural language specification, the LLM decomposes the intent into a logical sequence of steps, selects the appropriate tool for each, and executes them accordingly. Engineering fire design is often multi-turn interaction; hence, LangChain provides memory and context management to address this requirement by maintaining a persistent conversation history, thereby preventing the loss of contextual information. For example, if a user queries "What if the concrete cover were increased to 50 mm?", the agent must retrieve the column definition established in a prior turn, including its cross-section dimensions, reinforcement layout, and applied loading, to formulate a coherent comparative response.

As such, the proposed CFA agentic naturally support the Human-in-the-Loop mechanism with the recurrent cycle of Define → Analyse → Evaluate Eurocode Criteria → Refine. During the analysis process, the engineer may either approve the current design state, or reject it and provide corrective feedback, after which the agent re-enters the reasoning loop with the updated constraints. By doing so, any decisions in life-safety contexts still remain traceable to a responsible human actor.

### 2.3 Retrieval-augmented generation agent for standard compliance checking

To incorporate domain knowledge of RC column fire analysis into the agentic system, a Retrieval-Augmented Generation (RAG) [35] agent was developed and integrated into the CFA agentic framework. The agent retrieves relevant clauses, design equations, and tabular data from a curated document corpus, including EN 1992-1-2 (Eurocode 2: Structural Fire Design), ISO 834-1 (Standard Fire Exposure), and other technical documents regarding the structural behavior of RC columns at elevated temperatures. These documents detail the calculation procedures for load-bearing capacity analysis, material degradation, and fire resistance classification based on the computed thermal and mechanical results.

However, these technical documents present substantial challenges for conventional PDF parsers. Libraries such as PyPDF2 [36] operate on raw characters and fail to correctly reconstruct mathematical expressions, and they struggle to extract the Greek symbols that pervade the standard EN 1992-1-2. To address this limitation, the Marker library [37] was adopted for document parsing. Marker employs a pipeline of specialised models: the Surya model performs layout analysis, then identifies and delineates text blocks, tables, figures, and mathematical regions; the Texify model subsequently processes the identified equation regions and converts them to LaTeX notation; and a text extraction module reads the content blocks. The result is a structured Markdown representation that preserves the document's hierarchical organisation, mapping headings to sections and subsections, with equations rendered as LaTeX, tables formatted as aligned Markdown tables, and figures extracted with their associated captions. During chunking, clause boundaries are respected as segmentation units; for instance, the entirety of a section on the tabular method for columns is retained as a single chunk to preserve the interdependence of information. Each chunk is annotated with metadata recording its source document and section identifier.

The parsed Markdown chunks are encoded into dense vector representations using the Qwen3-Embedding-0.6B model developed by the Qwen Team at Alibaba Cloud [38]. Despite its relatively compact parameter count of 600 million, the model achieves state-of-the-art performance on the Massive Text Embedding Benchmark. A key advantage of this embedding model is its extended context window, which permits entire multi-page Eurocode sections to be encoded as a single vector, thereby preserving the logical flow of the information rather than treating isolated sentences as independent retrieval units. Furthermore, the model's ability to handle mathematical notation and symbolic content renders it well-suited to the formula-dense content of the fire design standard. The resulting embedding vectors are indexed using Facebook AI Similarity Search (FAISS) [39], an open-source library for efficient similarity search over large vector collections. FAISS organises vectors into quantised cells and, at query time, restricts the search to the cells most similar to the query vector using Hierarchical Navigable Small World graph traversal that progressively refines the search from a coarse global neighbourhood to a precise local one, thereby achieving sub-linear retrieval latency without exhaustive pairwise comparison. For each user query, the FAISS index retrieves the most semantically similar chunks from the document corpus. Query results are reported with explicit reference to the relevant Eurocode clause and equation number, along with attribution to the source document (EN 1992-1-2, ISO 834, or others). This structured output is exposed to the LLM orchestration layer and can be triggered conversationally through phrases such as "check against Eurocode" or "does the column achieve R90?".

### 2.4 Agent for thermal analysis

The thermal analysis using the Finite Element Method within the ANSYS [40] environment consists of three primary phases: pre-processing, solution, and post-processing (Fig. 4). In the pre-processing stage, the numerical model is established by defining the geometry of the column cross-section, assigning material properties, and generating an appropriate mesh. The temperature-dependent thermal properties of the material include thermal conductivity $k$, specific heat $c$, and density $\rho$. The thermal state within the section under investigation is governed by the nonlinear heat conduction equation:

$$\rho(T)c_p(T)\frac{\partial T}{\partial t} = \nabla\cdot\left(k(T)\nabla T\right) \quad (3)$$

The cross-section is discretized into heat-conduction finite elements (PLANE55), as shown in Fig. 5. Boundary conditions are applied to simulate fire exposure following the ISO 834 standard time–temperature curve, as given in Eq. (1). In the solution phase, the global conductivity and capacitance matrices are assembled to formulate the governing transient heat equilibrium equation:

$$\left[\boldsymbol{K}(T)\right]\{T\} + \left[\boldsymbol{C}(T)\right]\{\dot{T}\} = \boldsymbol{Q}(T) \quad (4)$$

where $[\boldsymbol{K}]$ is the conductivity matrix, $[\boldsymbol{C}]$ is the specific heat matrix, and $[\boldsymbol{Q}]$ is the thermal load vector. This equation is solved iteratively using a nonlinear transient solver based on the Newton–Raphson algorithm. In the post-processing phase, nodal temperature distributions $T(x, y, z)$ are extracted and visualized as isotherm contours, which facilitate the evaluation of the residual load-bearing capacity of the RC columns.

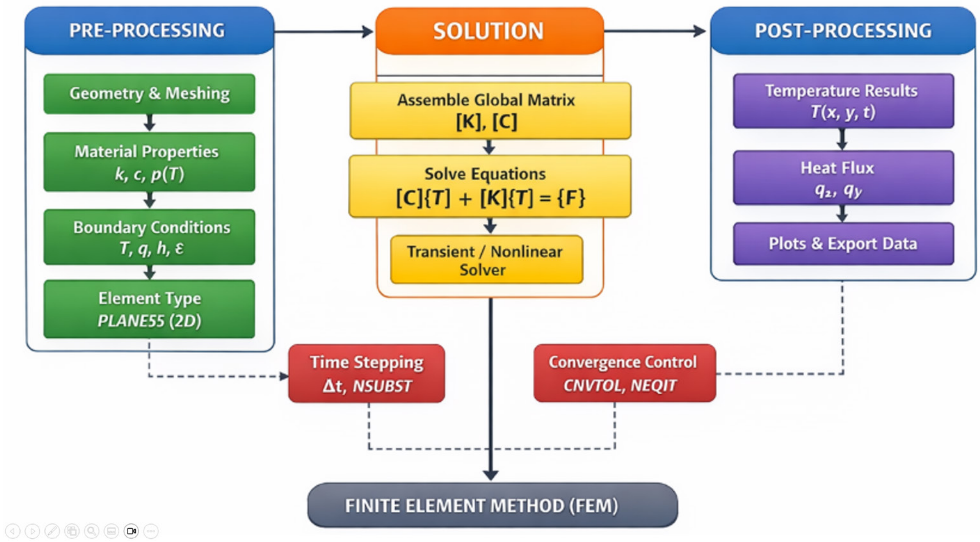



**Fig. 4** ANSYS computational diagram of thermal analysis

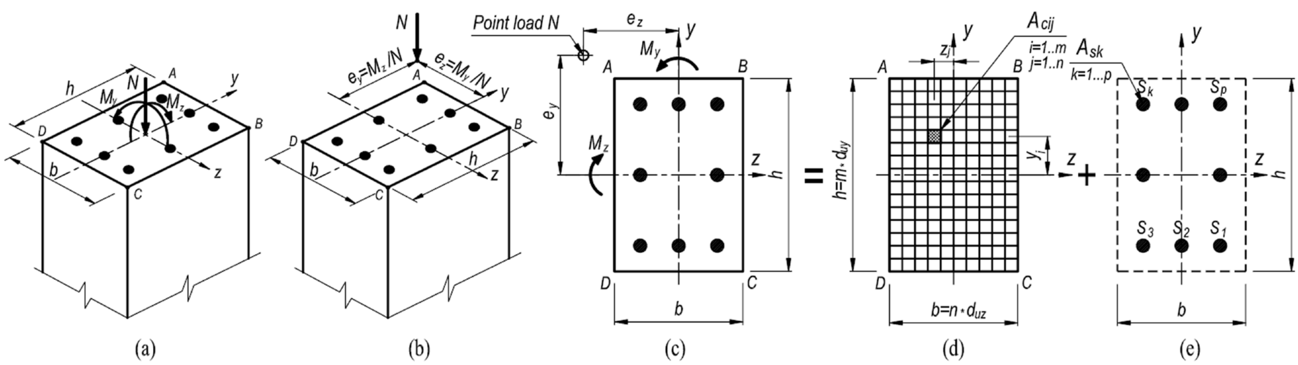



**Fig. 5** Modelling for sectional analysis of reinforced concrete columns in fire: (a) axial load and bending moments, (b) equivalent eccentricities, (c) column cross-section, (d) modelling of concrete, and (e) modelling of steel bars

### 2.5 Agent for fire resistance assessment of reinforced concrete columns

Once the temperature distribution is obtained, a Fire Resistance Assessment agent for RC columns, designated

CFire, is developed to determine the residual load-bearing capacity. The following assumptions are adopted: (1) concrete spalling is not considered in either the thermal or mechanical analyses; columns exhibiting conditions associated with elevated spalling risk are flagged accordingly; (2) the cross-sectional thermal analysis assumes a uniform temperature distribution along the column height; (3) only non-sway columns in braced structural systems are considered; and (4) the analysis is valid only when the load eccentricity does not exceed one-half of the corresponding cross-sectional dimension. Notably, the CFire agent is capable of translating natural-language engineering queries into structured computational workflows and providing interpretive reasoning over the resulting outputs.

The CFire agent operates through a sequential pipeline. In the first stage, the spatially distributed temperature field $T(x, y, z)$ at prescribed fire durations, obtained from ANSYS, is passed to the CFire agent, which performs a direct cross-sectional analysis to construct a series of $M$–$N$ interaction diagrams at discrete fire ratings ranging from ambient conditions (R0) through R30, R60, R90, R120, R150, R180, and R240. The material constitutive models adopted in this stage follow the temperature-dependent stress–strain relationships specified in Eurocode 2 for concrete and reinforcing steel, and in Eurocode 3 for structural steel. In the next stage, the ultimate axial resistance $N$ and the bending moment resistances $M_y$ and $M_z$ at each fire rating are computed. After that, the fire rating check tool compares the applied loading state, against the residual load-bearing capacity at successive fire durations, returning a pass/fail assessment together with the margin of safety and the predicted failure time.

It is noted that the equivalent rectangular compression zone method is difficult to apply in the analytical procedure for columns under fire conditions due to the non-uniform material degradation induced by the temperature distribution. To overcome this difficulty, the RC column cross-section is discretized into concrete elements and steel reinforcement elements (Fig. 5). The contribution of concrete to the load-bearing capacity is then obtained by integrating the mechanical compressive stresses over the compression zone. At a given temperature, the internal force generated by the concrete is calculated as follows:

$$F_{cc} = \int_{\Omega} \sigma^{\theta}_{cij} d\Omega; M^{\theta}_{cy} = \int_{\Omega} \sigma^{\theta}_{cij} z_i d\Omega; \quad M^{\theta}_{cz} = \int_{\Omega} \sigma^{\theta}_{cij} y_i d\Omega \tag{5}$$

in which Ω represents the compression zone and $z_i$, $y_j$ are the corresponding coordinates of the concrete elements. The concrete deformations are obtained by the following equation and visually depicted in Fig. 6.

$$\varepsilon^{\theta}_{u-ij} = \frac{c^{*}_{ij}}{c_n} \varepsilon^{\theta}_{tot-u} - \varepsilon^{\theta}_{th-ij} \tag{6}$$

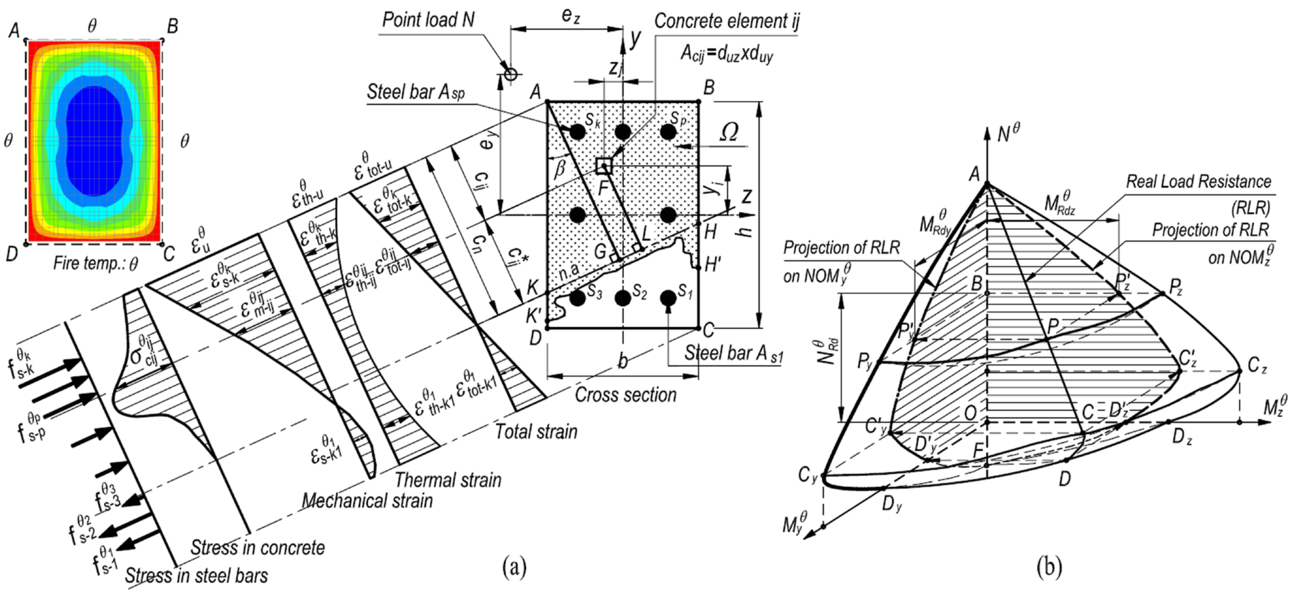



**Fig. 6** Calculation model for reinforced concrete columns' interaction diagrams in fire: (a) In-fre sectional analysis, and (b) In-fire sectional surface and diagrams

Next, the interaction diagram is construct based on the following equations.

$$N_{Rd}^{\theta} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sigma_{cij}^{\theta ij} d_{uy} d_u + \sum_{k_1=1}^{p_c} A_{sk_1}\left(f_{sck_1}^{\theta_{k_1}} - \sigma_{sck_1}^{\theta_{k_1}}\right) + \sum_{k_2=1}^{p-p_c} A_{sk_2} f_{sck_2}^{\theta_{k_2}} \quad (7)$$

$$M_{Rdy}^{\theta} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sigma_{cij}^{\theta ij} d_{uy} d_u z_j + \sum_{k_1=1}^{p_c} A_{sk_1}\left(f_{sck_1}^{\theta_{k_1}} - \sigma_{sck_1}^{\theta_{k_1}}\right) z_{k_1} + \sum_{k_2=1}^{p-p_c} A_{sk_2} f_{sck_2}^{\theta_{k_2}} z_{k_2} \quad (8)$$

$$M_{Rdz}^{\theta} = \sum_{i=1}^{m}\sum_{j=1}^{n}\sigma_{cij}^{\theta ij} d_{uy} d_u y_j + \sum_{k_1=1}^{p_c} A_{sk_1}\left(f_{sck_1}^{\theta_{k_1}} - \sigma_{sck_1}^{\theta_{k_1}}\right) y_{k_1} + \sum_{k_2=1}^{p-p_c} A_{sk_2} f_{sck_2}^{\theta_{k_2}} y_{k_2} \quad (9)$$

where $i, j$ are indices identifying the location of the compressed concrete elements; $k_1$, $k_2$ are indices identifying the location of the steel bars on the cross-section; $p$ is the total number of steel bars on the cross-section; $p_c$ is the total number of steel bars belonging to the compression zone; $z_j$, $y_j$ are the coordinates of the concrete elements on the cross-section; $z_k$, $y_k$ are the coordinates of the steel bars on the cross-section; $\sigma_{sc,k_1}^{\theta_{k_1}}$ is the compressive stress of the steel in the compression zone; $f_{sc,k_1}^{\theta_{k_1}}$ and $f_{sc,k_1}^{\theta_{k_2}}$ are the stresses of the steel in the compression zone and tension zone, respectively; and $\theta_{ij}$, $\theta_{k_1}$ , $\theta_{k_2}$ are the corresponding temperatures at each element.

The LLM component of the agent performs functions that extend beyond the deterministic capabilities of the numerical tools. Upon retrieval of the computational results, the LLM applies chain-of-thought reasoning to interpret the interaction diagram series and identify the critical fire duration at which the applied loading state first exceeds the residual cross-sectional capacity. Code compliance assessment is subsequently performed by cross-referencing the computed results against the simplified design provisions of Eurocode 2. Design recommendations are then generated based on the identified deficiencies, which may include increasing the longitudinal reinforcement ratio, enlarging the concrete cover, upgrading the aggregate type from siliceous to calcareous, or specifying supplementary fire-protective cladding. In addition to direct analysis, it is possible to equip CFire with data-driven surrogate models to rapidly estimate the column load-bearing capacity with high accuracy [41, 42].

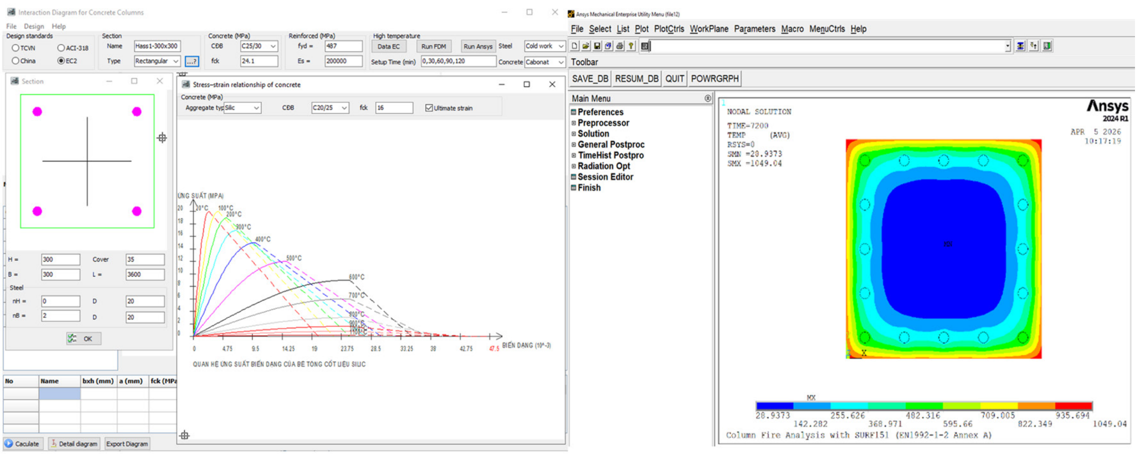
## 3 Case study

In this section, the applicability of the CFA agentic system is demonstrated through case studies as shown in Fig. 7.

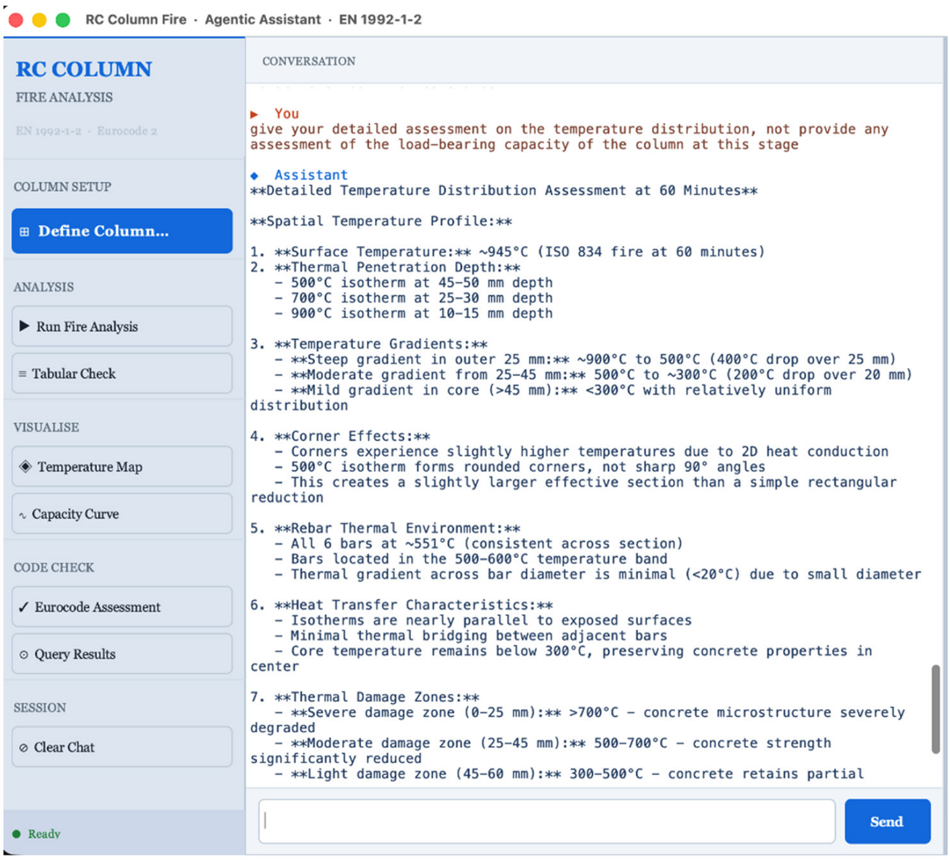
The first case study considers a 300 × 300 mm column with concrete compressive strength of $f_c$ = 24.1 MPa, reinforcing steel yield strength of $f_y$ = 487 MPa, six longitudinal rebars with 20 mm diameter (denoted as 6T20), 38 mm cover, and four-sided fire exposure. The CFA system accepts input data in two ways: via natural language in which the column attributes and their values are explicitly stated, or through a GUI for visual input, as shown in Fig. 7. The system then converts the input data into a script conforming to the ANSYS format and automatically establishes a connection to ANSYS to perform the thermal analysis, following the overall workflow described in Fig. 1.

Next, the thermal analysis using ANSYS Parametric Design Language (APDL), was carried out. The cross-section was discretized using a high-resolution mesh comprising PLANE55 elements, a 2D, 4-node planar elements in which each node possesses a single temperature degree of freedom. The material thermophysical parameters, including thermal conductivity, specific heat capacity, and density, were defined as nonlinear, temperature-dependent functions. For concrete, per EN 1992-1-2 (Annex A), thermal conductivity was modeled to decrease nonlinearly from 1.60 W/(m·K) at 20 °C to 0.50 W/(m·K) at 1200 °C. The specific heat formulation incorporated the moisture evaporation phase, characterized by a distinct peak of 2020 J/(kg·K) at 115 °C. For reinforcing steel, according to EN 1993-1-2, the specific heat capacity exhibits a sharp peak of 5000 J/(kg·K) at 735 °C before stabilizing at elevated temperatures.

A constant convective heat transfer coefficient of $c$ = 25 W/(m²·K) was adopted, and the emissivity of the concrete surface was taken as 0.7. The results of the thermal analysis are presented in the right panel of Fig. 7(a). One of the key advantages of the CFA agentic system is that it is equipped with expert knowledge through the RAG mechanism, enabling it to deliver insightful interpretation of analysis results beyond the plain numerical output typical of conventional software. Examples of such informative insights are highlighted in Fig. 7(b), including observations on thermal penetration depth, corner effects, rebar temperature evolution, and potential thermal damage zones. This information assists engineers in developing a deeper understanding of column behavior under fire exposure. Subsequently, the section analysis is performed automatically. In the background, the temperature distributions obtained from the thermal analysis at discrete fire durations (30, 60, 90, and 120 minutes) are exported as JSON-formatted text files, which are then passed to the CFire agent for section capacity analysis. Based on Eq. (7),




(a)




(b)

**Fig. 7** Thermal analysis results including quantitative and qualitative results: (a) Calculation of temperature distribution, and (b) Qualitative assessment by the CFA agent based on expert knowledge

the CFire agent generates the corresponding *M–N* interaction diagrams for the column at each fire duration under investigation, as shown in Fig. 8. The figure presents the *M–N* interaction curves for fire resistance ratings R0, R30, R60, R90, and R120.

To validate the results, a comparison with results of the fire tests on reinforced concrete columns conducted by Hass [5], which was also used for validation by Barmonte et al. [12], is presented in Fig. 9.

In the experiment on an RC column having square cross section of 300 × 300 (mm) and 6T20 longitudinal rebars, respetive concrete and reinforcing steel strengths of $f_c$ = 24.1 MPa, $f_y$ = 487 MPa, structural failure of the column was observed after 86 minutes of ISO 834 fire

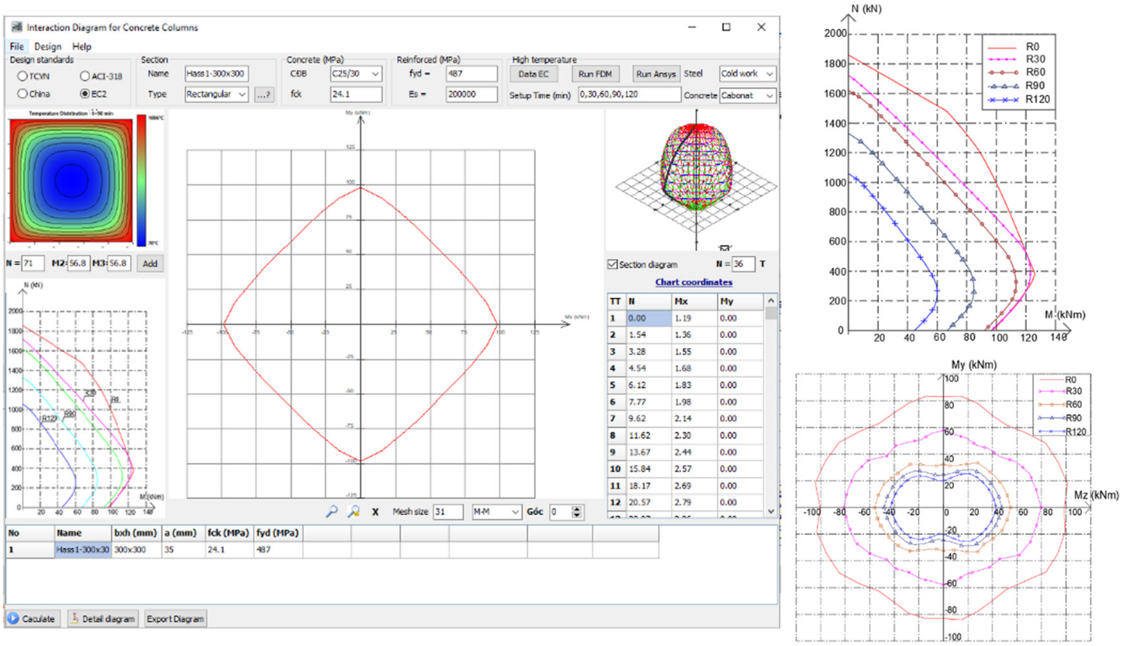



**Fig. 8** Interaction diagram obtained by the fire agent in the CFA agentic system

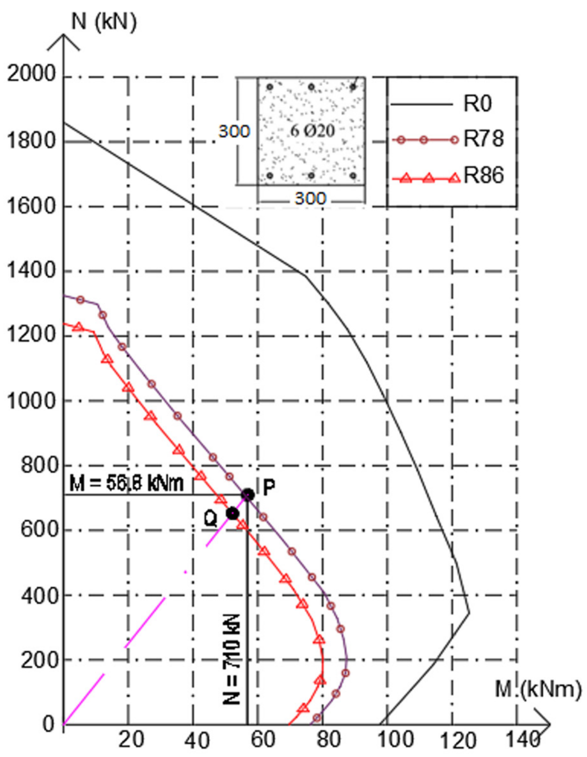



**Fig. 9** Validation of calculated results by comparison with existing experimental results

exposure with the recorded axial load of 710 kN and a bending moment of 56.8 kN·m [5, 12]. On the other hand, the CFA agentic system generates an axial load–bending moment interaction diagram in which the coordinate represents the axial compressive load and the abscissa represents the bending moment. The interaction curve defines the load-bearing capacity envelope of the column. As temperature increases over time, the column's load-bearing capacity undergoes progressive degradation. Based on the interaction diagram at 86 minutes of fire exposure (R86), the applied experimental load, represented by point P having coordinates $M = 56.8$ kN·m and $N = 710$ kN, falls outside the capacity envelope, correctly indicating structural failure consistent with the experimental observation. More specifically, the computational module predicts structural failure at $t = 78$ min, whereas the experimentally recorded failure time is $t_{exp} = 86$ min. These results demonstrate that the developed module achieves good agreement with the experimental data while providing a conservative, safe-side prediction of failure time.

The accuracy is quantified by the coefficient $k$ = OP/OQ = 0.92, where OP and OQ are the respective distances from the origin point O to point P ($M = 56.8$ kN·m, $N = 710$ kN), and to point Q, which is the intersection of line OP and the R86 interaction curve (Fig. 9).

Subsequently, the CFA agentic system provides both quantitative and qualitative assessments of the reduction in *M–N* interaction diagrams, as shown in Figs. 10 and 11.

In particular, the agentic framework demonstrates advanced diagnostic capabilities by identifying the governing failure mechanisms. The overall contraction of the *M–N* interaction boundary is attributed to thermo-mechanical phenomena, including the loss of effective concrete cross-section and the temperature-dependent reduction in yield strength. In addition, the CFA agent

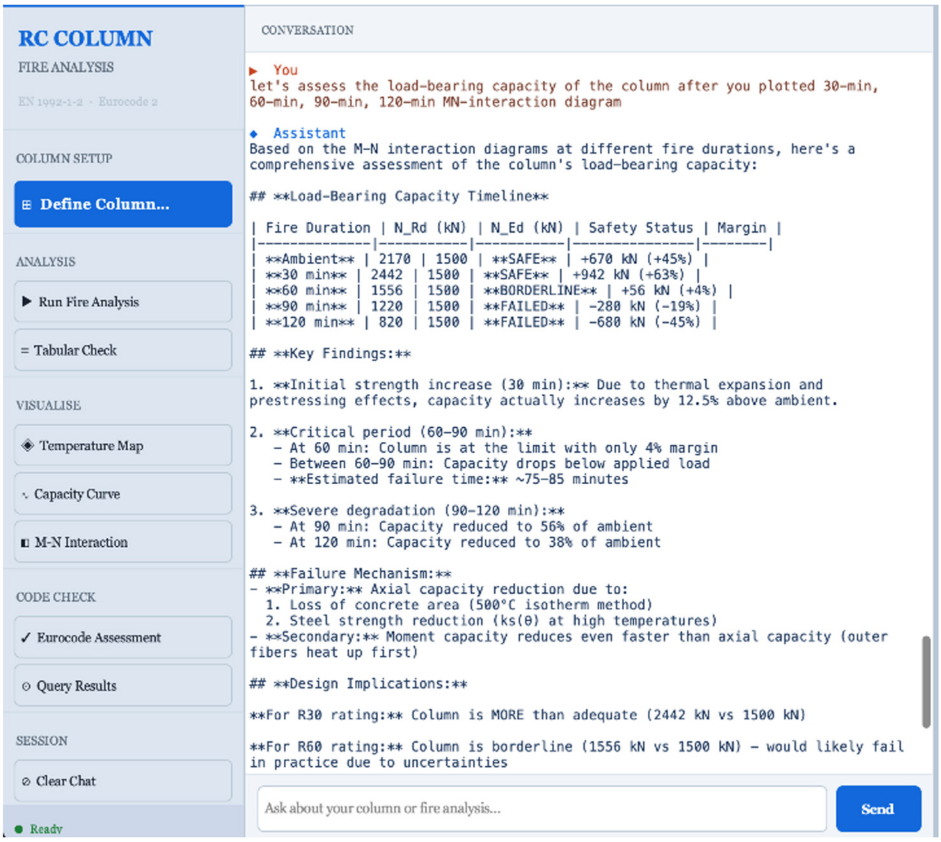



**Fig. 10** Insights provided by CFA for calculated interaction diagram for different temperature

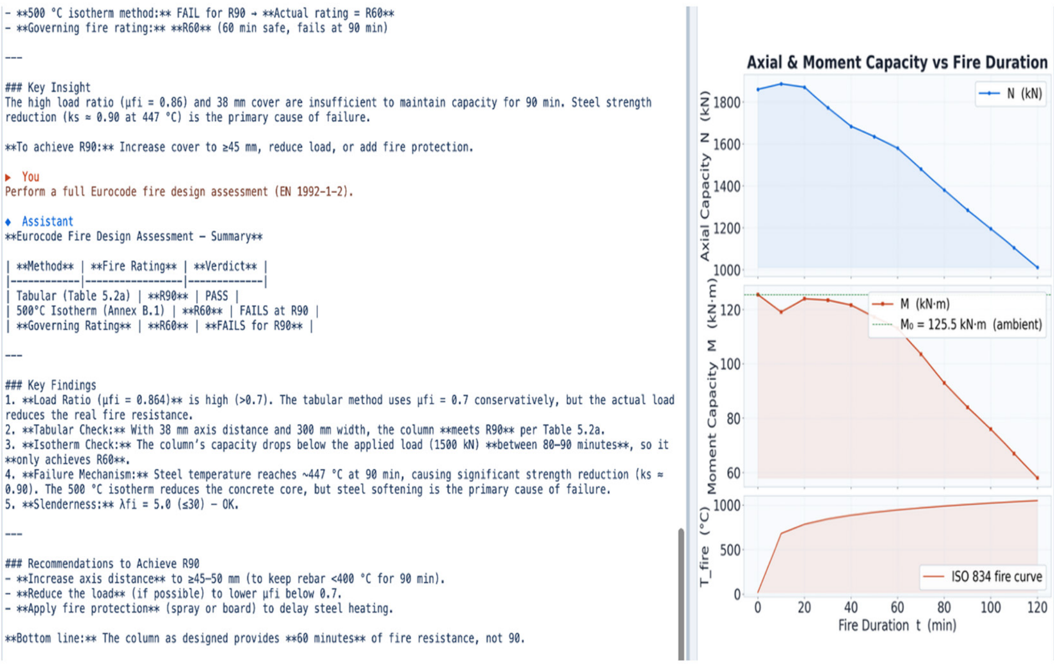



**Fig. 11** Evolution of the axial and moment capacity against fire duration

correctly identifies a secondary phenomenon whereby the moment-bearing capacity degrades at a faster rate than the axial capacity. For instance, at R30, $M_{max} \approx 120$ kN·m and $N_{max} = 1700$ kN, whereas at R120, these values reduce to $M_{max} \approx 60$ kN·m and $N_{max} = 1050$ kN. This behavior is also correctly explained by the agent as a consequence of the rapid heating of the outermost structural fibers. Such diagnostic capability is achieved through the reasoning capacity of the LLM orchestrator augmented by the RAG agent, which equips the system with domain-specific expert knowledge. Subsequently, the system proposes prescriptive recommendations, including increasing the cover, resizing the cross-section, adding supplementary reinforcement bars, or applying appropriate fire protection measures.

Next, to demonstrate the generalisability and robustness of the proposed framework, the CFA agentic system is applied to various RC columns with different cross-sections, such as 220 × 400 with longitudinal reinforcement of 4T25, 300 × 500 with 8T25, 500 × 500 with 16T25, and 1000 × 1000 with 32T25, as shown in Fig. 12.

For each section, the CFA agentic system applies the overall workflow in Fig. 1 and a similar process to that explained above to automatically perform thermal analysis, establish an interaction diagram, and plot capacity curves. Users simply provide inputs to CFA via natural language.

Previous studies have primarily examined temperature fields using isotherms at specific intervals (30, 60, 90, 180,

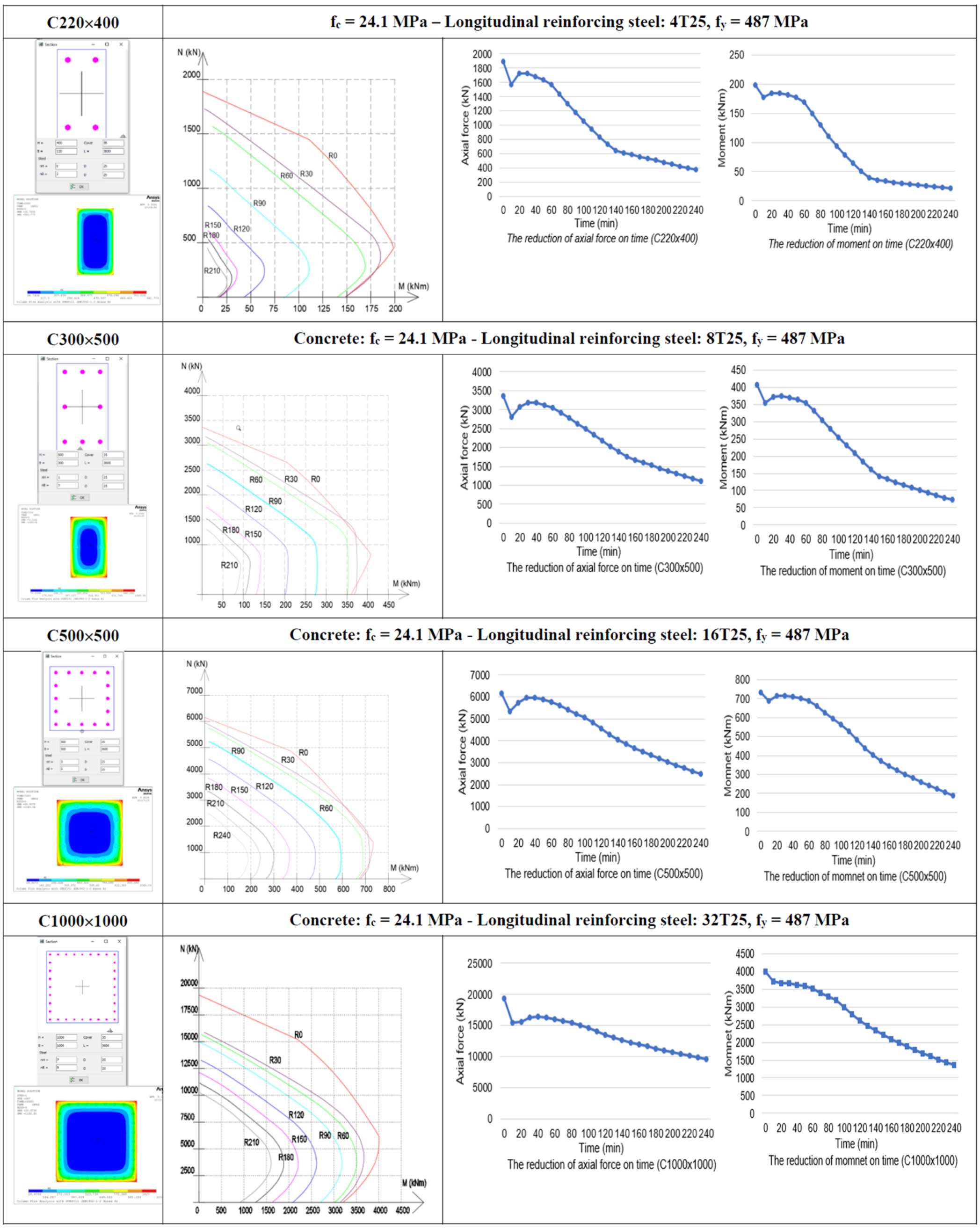



**Fig. 12** Load-bearing analysis results for various RC columns in fire by CFA

and 240 minutes) under standard fire conditions for a finite selection of rectangular (80 × 150, 160 × 300, 300 × 300, 300 × 600, and 500 × 800 mm) and circular (D300 mm) reinforced concrete (RC) cross-sections. However, the presented workflow and CFA allow load-bearing analysis of rectangular columns in fire with arbitrary cross-sectional sizes and at any time points. The figure clearly shows the critical influence of cross-sectional size on a structural member's failure; as the slender 220 × 400 mm column experiences rapid, near-linear capacity loss, the massive square 1000 × 1000 mm column can considerably maintain its initial capacity for the 120-minute duration. These results demonstrate that an automated agentic system like CFA enables researchers and engineers to explore highly customised structural elements in fire conditions with operational simplicity.

Although the system prompt in this study enforces a specific execution sequence (Data Ingestion → ANSYS Thermal → EC Calculation → Interaction Diagram), this constraint is a physical and domain-specific necessity rather than a limitation of the AI's autonomy. This is because, in structural fire engineering, the degraded load-bearing capacity cannot be evaluated before the spatial, time-dependent temperature field is known: the strength-reduction factors, the remaining effective cross-section, and the elevated-temperature *N–M* interaction envelope are all explicit functions of the temperature distribution computed in the preceding step. The Data Ingestion → Thermal Analysis → Capacity Computation → Interaction Diagram ordering, therefore, encodes the causal dependency of the underlying physics; enforcing it guarantees that the agent never reports a capacity that is not grounded in a valid temperature field.

However, the "agentic" and "autonomous planning" abilities of the proposed CFA approach extend beyond traditional static, hard-coded pipelines through an interactive, context-aware process. Rather than blindly executing a script, the agent autonomously maps natural language inputs to formal ontologies, selects the appropriate specialized tools to invoke, processes the observations returned by those tools, and synthesizes human-readable insights. The agent exhibits dynamic reasoning that dictates and alters the execution path in several specific scenarios. For instance, if the finite element solver (ANSYS) fails to converge or export data, the agent alters the execution path by dynamically pausing the sequence, clearly stating the error, and suggesting remedial steps to the user, such as mesh refinement or time-step adjustments. Furthermore, the agent can alter its task execution based on persistent conversational memory. If an engineer provides corrective feedback or asks a hypothetical follow-up question (e.g., "What if the concrete cover were increased to 50 mm?"), the agent uses context management to bypass initial setup steps, dynamically retrieving the established column definition and altering its path to formulate a coherent comparative analysis.

## 4 Conclusions

In this study, a novel agentic system has been proposed, designed, and implemented to automate the multi-stage workflow for assessing the load-bearing capacity of reinforced concrete columns under elevated temperatures. The CFA system seamlessly integrates different agents for ingesting column geometry and material data; performing heat transfer simulations under ISO 834 standard fire exposure using ANSYS; constructing axial force–biaxial bending moment interaction diagrams; evaluating residual load-bearing capacity; and interpreting calculated results based on expert knowledge through retrieval-augmented generation. The proposed system enables practitioners to move beyond conventional, rigid, script-based pipelines that require the manual transfer of data between disparate software environments, such as finite element thermal solvers, in-house sectional analysis programs, and spreadsheet-based code-checking tools.

With CFA, users can smoothly interact with AI agents via natural language, via an LLM-based orchestrator that delegates tasks to corresponding specialised AI agents.

With such an interactive environment, the Human-in-the-Loop decision is inherently integrated in CFA, ensuring that safety-critical evaluations conform to domain expertise and remain under the authorisation of professional engineers. In summary, the practitioner's role shifts from that of a manual data operator to that of an intelligent orchestrator of AI agents, significantly reducing the repetitive effort and technical burden in data interchange across the thermal–structural analysis chain, thus enabling professionals to concentrate on fire safety design exploration and overall performance optimisation.

In future work, it is desirable to extend the agentic framework to other structural elements, including concrete-encased steel columns, steel beams, and others, in conformity with other design codes such as LRFD-AISC [43]. Furthermore, it is highly desirable to conduct future physical fire experiments encompassing diverse and complex column shapes, as well as those utilizing new or recycled materials. These datasets will be instrumental in validating and extending the current capabilities of the CFA agentic method. On the other hand, the current version of the CFA agentic system relies mainly on text-based and structured JSON interactions; future development could equip the agentic system with multimodal models that would allow the system to directly interpret architectural and structural drawings, thereby creating a more seamless and intuitive Human-in-the-Loop experience.

**Acknowledgement**
The research presented in this article is supported by Hanoi University of Civil Engineering (HUCE), under grant number 42-2025/KHXD-TD.

**Appendix**
Table A1 summarizes the computational overhead of the CFA's components, which comprise column definition, thermal analysis, Eurocode assessment, and visualisation.

For each component, two language-model calls, one to select the appropriate tool and one to execute it, are typically invoked. Token consumption is dominated by the input (23519 tokens) relative to the output (2397 tokens), as is expected for tool-augmented generation, wherein the model must process the tools' outputs alongside retrieved context. The assessment phase carries the heaviest load (8276 input tokens, 897 output tokens, 8.6 s) because this stage injects retrieved normative clauses into the prompt via the RAG pipeline; the remaining phases are considerably lighter. The complete cycle requires 25.5 s of language-model processing time. Overall, the orchestration layer introduces an acceptable computational overhead for an interactive design assistant.

To demonstrate the contribution of the retrieval component, we posed a query to the orchestrator with retrieval both disabled and enabled (deepseek-chat, T = 0) (Table A2). Without RAG, the orchestrator returned plausible but incorrect minimum axis distances (200/25, 250/30); with RAG, it reproduced the standard's exact values (200/32, 300/27; 250/46, 350/40), grounded in the retrieved clause. In fire design, the axis distance governs rebar protection; therefore, the ungrounded error is unconservative. In other words, without retrieval, the model produced incorrect minimum axis distances and an incomplete set of dimension pairs; with retrieval, it reproduced the exact tabulated values. This confirms that the role of RAG in the CFA is to ground safety-critical normative values and suppress confident hallucinations, rather than to alter deterministic engineering computations.

To quantify the performance of the retrieval stage, we constructed a benchmark of twelve representative queries spanning the system's question families (tabular method, 500 °C isotherm method, material strength-reduction factors, thermal properties, slenderness, load ratio, standard fire curve, and experimental corpus). Each query was labeled with two ground-truth targets: its governing source document (EN 1992-1-2, ISO 834-1, or the reference thesis) and its specific governing clause (e.g., Table 5.2a, Annex B.1, §3.3). The complete labeling is provided in Table A3. Retrieval quality is reported using two standard information-retrieval metrics. Hit_k denotes the proportion of queries for which a correct passage appears within the top k returned results; thus, Hit_1 measures how often the initial retrieved passage is correct, and Hit_3 indicates how often a correct passage appears among the top three. The mean reciprocal rank (MRR) is the average, computed over all queries, of the reciprocal of the rank at which the first correct passage appears (1/rank). It ranges from 0 to 1, with a value of 1.0 indicating that the correct passage is consistently retrieved in the first position. Evaluated at the document level, the retriever attained Hit_1=0.92, Hit_3=1.00, and MRR=0.96. These

**Table A1** Computation resources consumed by the CFA's components

| Tool | LLM calls | In-token | Out-token | LLM (s) | Tool |
|---|---|---|---|---|---|
| Define | 2 | 3,797 | 508 | 5.6 | define_column |
| Analyse | 2 | 4,615 | 457 | 5.4 | run_fire_analysis |
| Assess | 2 | 8,276 | 897 | 8.6 | assess (RAG) |
| Plot | 2 | 6,831 | 535 | 5.9 | plot_capacity_curve |
| Total | 8 | 23,519 | 2,397 | 25.5 | |

Notes: Each function requires two LLM calls: one for tool selection and one for tool execution.

**Table A2** Example of RAG impact on a Eurocode-grounded answer

| | R30 | R60 | Verdict |
|---|---|---|---|
| Without RAG (model memory) | 200/25 | 250/30 | ✗ axis distances wrong, only one pair each |
| With RAG (clause retrieved) | 200/32, 300/27 | 250/46, 350/40 | ✓ exact + complete |

Question: Per EN 1992-1-2 Table 5.2a, for columns exposed on more than one side, give the minimum (width / axis distance) pairs for R30 and R60.
Ground truth (from the retrieved Table 5.2a):
R30 → 200/32, 300/27 · R60 → 250/46, 350/40

**Table A3** Retrieval benchmark: queries, expected sources, ground-truth clauses, and retrieval ranks (document/clause)

| # | Query | Expected source | Ground-truth clause | doc rank | clause rank |
|---|---|---|---|---|---|
| 1 | Minimum column width / axis distance for R90, tabular method | EN 1992-1-2 | §5.3.2 Method A, Table 5.2a | 1 | 2 |
| 2 | 500 °C isotherm method, effective reduced section | EN 1992-1-2 | Annex B.1 (500 °C isotherm method) | 1 | 1 |
| 3 | Concrete strength reduction factor $k_c(\theta)$ | EN 1992-1-2 | §3.2.2.1 & Table 3.1; design §4.2.4.2 | 2 | 2 |
| 4 | Steel yield reduction factor $k_s(\theta)$ | EN 1992-1-2 | §3.2.3 & Table 3.2a; design §4.2.4.3 | 1 | 1 |
| 5 | Column slenderness / buckling / 2nd-order in fire | EN 1992-1-2 | Annex B.3 / §5.3.3 (buckling) | 1 | 1 |
| 6 | Load ratio $\mu_{fi}$, partial factor | EN 1992-1-2 | §2.4.2 ($\mu_{fi}$) & §2.3 ($\gamma_{M,fi}$) | 1 | 1 |
| 7 | Thermal conductivity / specific heat / density vs T | EN 1992-1-2 | §3.3 (3.3.1–3.3.3) | 1 | 1 |
| 8 | Standard time–temperature fire curve | ISO 834 | ISO 834-1 §5.1 furnace (standard) curve | 1 | 1 |
| 9 | Fire-resistance criteria, R rating, load-bearing | ISO 834 | ISO 834-1 performance / load-bearing capacity (R) | 1 | 1 |
| 10 | Experimental failure time, verification, agreement ratio | Thesis | §8.8 Experimental Verifications (Tables 8.5–8.13) | 1 | 1 |
| 11 | Inclined neutral axis, biaxial interaction diagram | Thesis | §9.6.2 / §8.4 cross-sectional analysis | 1 | 1 |
| 12 | Transient creep / thermal strain model | Thesis | Constitutive model: $\varepsilon_{tot} = \varepsilon_{th} + \varepsilon_{\sigma} + \varepsilon_{cr} + \varepsilon_{tr}$ | 1 | 1 |

Notes: Measurement metrics: Hit_1=0.92, Hit_3=1.0, MRR=0.96

results confirm that the RAG retrieval achieves high accuracy, demonstrating that the system dependably identifies the relevant code clauses required to support its fire-design compliance checks.

A reliable natural-language interface must map semantically equivalent requests to the same action, regardless of their specific wording. To evaluate this capability, we selected five tool intents (run fire analysis, plot temperature profile, tabular-method check, full Eurocode assessment, and capacity-curve plot) and issued each using four distinct paraphrases (20 requests in total) (Table A4). The orchestrator successfully routed all 20 requests to the correct tool (routing accuracy = 100%; intent consistency = 5/5) and extracted every numeric argument correctly (8/8). Consequently, paraphrases such as "run the fire analysis for 120 minutes," "carry out the fire exposure analysis up to two hours," and "compute the heat-transfer and capacity analysis over 120 minutes" all resolved to the same tool call with identical parameters. These results indicate that the language-model orchestrator interprets user intent robustly and remains resilient to variations in surface phrasing.

**Table A4** Tool-invocation robustness: paraphrased natural-language commands mapped to each computational tool

| # | Tool (function call) | Example natural-language commands |
|---|---|---|
| 1 | run_fire_analysis<br>(expected arg: time = 120 min) | "Run the fire analysis for 120 minutes."<br>"Carry out the fire exposure analysis up to 120 min."<br>"Compute the heat-transfer and capacity analysis for two hours."<br>"Perform the fire response calculation over 120 minutes." |
| 2 | plot_temperature_profile<br>(expected arg: time = 60 min) | "Plot the temperature distribution at 60 minutes."<br>"Show the cross-section heat map after 60 min of fire."<br>"Draw the thermal field in the section at t = 60 min."<br>"Display the section temperatures at one hour of exposure." |
| 3 | check_tabular_method | "Check the tabular method."<br>"Run the EN 1992-1-2 Table 5.2a tabular check."<br>"Verify fire resistance using the tabulated data method."<br>"Does the column pass the tabular method?" |
| 4 | assess_eurocode_fire_compliance | "Do a full Eurocode fire assessment."<br>"Run a complete EN 1992-1-2 fire compliance check."<br>"Assess whether the column complies with Eurocode fire provisions."<br>"Give me the full fire design assessment." |
| 5 | plot_capacity_curve | "Plot the capacity curve."<br>"Show how the load-bearing capacity drops with fire duration."<br>"Graph $N_{Rd}$ against time."<br>"Plot the axial capacity versus fire time." |

## References


[1] Lie, T. T, Celikkol, B. "Method to Calculate the Fire Resistance of Circular Reinforced Concrete Columns", Materials Journal, 88(1), pp. 84–91, 1991. https://doi.org/10.14359/2412

[2] Lie, T. T., Irwin, R. J. "Method to Calculate the Fire Resistance of Reinforced Concrete Columns with Rectangular Cross Section", ACI Structural Journal, 90(1), pp. 52–60, 1993. https://doi.org/10.14359/4210

[3] Dotreppe, J. C., Franssen, J. M, Vanderzeypen, Y. "Calculation Method for Design of Reinforced Concrete Columns under Fire Conditions", ACI Structural Journal, 96(1), pp. 9–18, 1999. https://doi.org/10.14359/591

[4] Dotreppe, J. C., Franssen, J. M., Bruls, A. "Experimental Research on the Determination of the Main Parameters Affecting the Behaviour of Reinforced Concrete Columns under Fire Conditions", Magazine of Concrete Research, 49(179), pp. 117–127, 1996. https://doi.org/10.1680/macr.1997.49.179.117

[5] Hass, R. "Practical Rules for the Design of Reinforced Concrete and Composite Columns Submitted to Fire", Institute für Baustoffe, Massivbau und Brandschutz der Technischen Universität Braunschweig, 1986.

[6] Lie, T. T., Woollerton, J. L. "Fire Resistance of Reinforced Concrete Columns: Test results", National Research Council, Canada, 1988.

[7] Tang, C. Y. "An Interactive Formula for Fire Resistance of Columns", Master's Thesis, Nanyang Technological University, Singapore, 2001.

[8] Kodur, V., Wang, T. C., Cheng, F. P. "Predicting the Fire Resistance Behaviour of High Strength Concrete Columns", Cement and Concrete Composites, 26(2), pp.141–153, 2004. https://doi.org/10.1016/S0958-9465(03)00089-1

[9] Tan, K. H, Yao, Y. "Fire Resistance of Reinforced Concrete Columns Subjected to 1-, 2-, and 3-face Heating", Journal of Structural Engineering, 130(11), pp. 1820–1828, 2004. https://doi.org/10.1061/(ASCE)0733-9445(2004)130:11(1820)

[10] Bratina, S., Čas, B., Saje, M., Planinc, I. "Numerical Modelling of Behaviour of Reinforced Concrete Columns in Fire and Comparison with Eurocode 2", International Journal of Solids and Structures, 42(21–22), pp. 5715–5733, 2005. https://doi.org/10.1016/j.ijsolstr.2005.03.015

[11] Kodur, V., Raut. N. "A Simplified Approach for Predicting Fire Resistance of Reinforced Concrete Columns under Biaxial Bending", Engineering Structures, 41, pp. 428–443, 2012. https://doi.org/10.1016/j.engstruct.2012.03.054

[12] Barmonte, P., Monte, F. L. "Reinforced concrete columns exposed to standard fire: Comparison among different constitutive models for concrete at high temperature", Fire Safety Journal, 71, pp. 310–323, 2015. https://doi.org/10.1016/j.firesaf.2014.11.014

[13] Nguyen, T. T., Tan, K. H. "A simplified analysis method on reinforced concrete columns subjected to uniaxial bending in fire", In: Proceedings of the Fifth International Conference on Design and Analysis of Protective Structures (DAPS), Singapore, 2015, pp. 1053–1063.

[14] European Committee for Standardization "EN 1992-1-2: Eurocode 2: Design of concrete structures - Part 1-2: General rules - Structural fire design", CEN, Brussels, Belgium, 2004.

[15] Tan, K. H., Nguyen, T. T. "Structural responses of reinforced concrete columns subjected to uniaxial bending and restraint in fire", Fire Safety Journal, 60, pp. 1–13, 2013. https://doi.org/10.1016/j.firesaf.2013.04.005

[16] Tan, K. H., Nguyen, T. T. "Experimental behaviour of reinforced concrete columns subjected to biaxial bending and restraint at elevated temperatures", Engineering Structures, 56, pp. 823–836, 2013. https://doi.org/10.1016/j.engstruct.2013.06.013

[17] Nguyen, T. T., Tan, K. H. "Simplified fire-resistant analysis of reinforced concrete columns under biaxial bending to EC2-1.2", In: Proceedings of the 7th International Conference on Protection of Structures against Hazards (PSH18), Hanoi, Vietnam, pp. 425–436, 2018.

[18] Kaveh, A., Ghazaan. M. I., Mohammadi, A. "Seismic Response Prediction of 3D Reinforcement Concrete Frames Using Machine Learning Methods", Periodica Polytechnica Civil Engineering, 70(1), pp. 76–95, 2026. https://doi.org/10.3311/PPci.42282

[19] Kaveh, A., Eskandari, A., Piri, M. "Metaheuristic-optimized Machine Learning for Mechanical Property Prediction in Eco-friendly Rubberized Concrete", Periodica Polytechnica Civil Engineering, 69(4), pp.1124–1148, 2025. https://doi.org/10.3311/PPci.41258

[20] Fawad, M., Salamak, M., Poprawa, G., Janas, Y. "Automation of structural health monitoring (SHM) system of a bridge using BIMification approach and BIM-based finite element model development", Scientific Reports, 13(1), 13215, 2023. https://doi.org/10.1038/s41598-023-40355-7

[21] Sebastian, K., Huaccha, M., Rosales, B. "Application of AI for modelling and structural analysis of a parametric 2D frame with voice assistant", E3S Web Conferences, 586, 02003, 2024. https://doi.org/10.1051/e3sconf/202458602003

[22] Nguyen, T. T., Dang., V. H., Pham, T. T. "Development of an automatic and knowledge-infused framework for structural health monitoring based on prompt engineering", Frontiers of Structural and Civil Engineering, 18(11), pp. 1752–1774, 2024. https://doi.org/10.1007/s11709-024-1118-7

[23] Xiahou, X., Chen, G., Li, Z., Xu, X., Li. Q. "Knowledge Management in Construction Quality Management: Current State, Challenges, and Future Directions", IEEE Transactions on Engineering Management, 72, pp. 1069–1088, 2025. https://doi.org/10.1109/TEM.2025.3550354

[24] Zheng, Z., Han, J., Chen, K. Y., Cao, X. Y., Lu, X. Z., Lin, J. R.. "Translating regulatory clauses into executable codes for building design checking via large language model driven function matching and composing", Engineering Applications of Artificial Intelligence, 163, 112823, 2026. https://doi.org/10.1016/j.engappai.2025.112823

[25] Hope, B., Bracey, J., Choukir, S., Warner, D. "Assessment of ChatGPT for Engineering Statics Analysis", [preprint] arXiv, 1 February 2025. https://doi.org/10.48550/arXiv.2502.00562

[26] Abou Ali, M., Dornaika, F., Charafeddine, J. "Agentic AI: A comprehensive survey of architectures, applications, and future directions", Artificial Intelligence Review, 59(1), 11, 2026. https://doi.org/10.1007/s10462-025-11422-4

[27] Li, Z., Wang, Z., Wang, W., Hung, K., Xie, H., Wang, F. L. "Retrieval-augmented generation for educational application: A systematic survey", Computers and Education: Artificial Intelligence, 8, 100417, 2025. https://doi.org/10.1016/j.caeai.2025.100417

[28] Li, M., Wang, Z. "BuildingGPT: Query building semantic data using large language models and vector-graph retrieval-augmented generation", Building and Environment, 287, 113855, 2026. https://doi.org/10.1016/j.buildenv.2025.113855

[29] Model Context Protocol "What is the Model Context Protocol (MCP)?", [online] Available at: https://modelcontextprotocol.io/docs/getting-started/intro [Accessed: 7 April 2026]

[30] Li, H., Xu, Y., Hong, T. "EnergyPlus-MCP: A model-context-protocol server for ai-driven building energy modeling", SoftwareX, 32, 102367, 2025. https://doi.org/10.1016/j.softx.2025.102367

[31] ISO "ISO 834-1:2025 - Fire-resistance tests – Elements of building construction – Part 1: General requirements", International Organization for Standardization, Geneva, Switzerland, 2025.

[32] DeepSeek-AI, Liu, A., Feng, B., Xue, B., Wang, B., …, Pan, Z. "DeepSeek-V3 Technical Report", [preprint] arXiv, 18 February 2025. https://doi.org/10.48550/arXiv.2412.19437

[33] Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K., Cao, Y. "ReAct: Synergizing Reasoning and Acting in Language Models", [preprint] arXiv, 10 March 2023. https://doi.org/10.48550/arXiv.2210.03629

[34] LangChain "Observe, Evaluate, and Deploy Reliable AI Agents" [online] Available at: https://www.langchain.com/ [Accessed: 7 April 2026]

[35] Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., ..., Kiela, D. "Retrieval-Augmented Generation for Knowledge-intensive NLP Tasks", [preprint], arXiv, 12 April 2021. https://doi.org/10.48550/arXiv.2005.11401

[36] PyPDF2 "PyPDF2 documentation", [online] Available at: https://pypdf2.readthedocs.io/en/3.x/ [Accessed: 7 April 2026]

[37] Paruchuri, V. "Marker: Convert PDF to markdown + JSON quickly with high accuracy", GitHub repository, 2024. Available at: https://github.com/datalab-to/marker [Accessed: 26 March 2026]

[38] Zhang, Y., Li, M., Long, D., Zhang, X., Lin, H., …, Zhou, J. "Qwen3 Embedding: Advancing Text Embedding and Reranking Through Foundation Models", [preprint] arXiv, 11 June 2025. https://doi.org/10.48550/arXiv.2506.05176

[39] Johnson, J., Douze, M., Jegou, H. "Billion-Scale Similarity Search with GPUs", IEEE Transactions on Big Data, 7, pp. 535–547, 2021. https://doi.org/10.1109/TBDATA.2019.2921572

[40] Thompson, M. K., Thompson, J. M. "ANSYS mechanical APDL for finite element analysis", Butterworth-Heinemann, 2017. ISBN 978-0128129814

[41] Kaveh, A. "Applications of artificial neural networks and machine learning in civil engineering", Springer Cham, 2024. ISBN 978-3-031-66051-1 https://doi.org/10.1007/978-3-031-66051-1

[42] Kaveh, A., Eskandari, A., Movasat, M. "Buckling resistance prediction of high-strength steel columns using metaheuristic-trained artificial neural networks", Structures, 56, 104835, 2023. https://doi.org/10.1016/j.istruc.2023.07.043

[43] Kaveh, A., Talatahari, S. "Charged system search for optimum grillage system design using the LRFD-AISC code", Journal of Constructional Steel Research, 66(6), pp. 767–771, 2010. https://doi.org/10.1016/j.jcsr.2010.01.007