JOURNAL OF SOFT COMPUTING AND DATA MINING
e-ISSN: 2716-621X

JSCDM

Vol. 6 No. 3 (2025) 403-415
https://publisher.uthm.edu.my/ojs/index.php/jscdm

Computational Modelling and Smart Integration of Bio-Inspired Systems for Enhanced Wireless Localization Using Wearable Sensors

Elaf Ali Alsisi[1,2], Mahmoud Mohamed Bahloul[3], Mohammed Salah Khaleel[4], Mohammed Ali Mahgoub Elneel[4], Omer Eltag Mohammed Elhag[5], Mohamed M.Abbassy[6]*

[1] *Business Informatics Department, College of Business, King Khalid University, Abha, SAUDI ARABIA*
[2] *Center of Artificial Intelligence, King Khalid University, Abha, SAUDI ARABIA*
[3] *Business Information Systems Department, Faculty of Commerce and Business Administration, Helwan University, Cairo, EGYPT*
[4] *Inaya Medical Colleges, Al Qirawan, Riyadh 13541, SAUDI ARABIA*
[5] *Business Informatics Department, College of Business, King Khalid University, Abha, SAUDI ARABIA*
[6] *Faculty of Computers and Artificial Intelligence, Beni-Suef University, EGYPT*

*Corresponding Author: mmabbassy@fcis.bsu.edu.eg
DOI: https://doi.org/10.30880/jscdm.2025.06.03.025

Article Info

Received: 9 October 2025
Accepted: 10 December 2025
Available online: 30 December 2025

Keywords

Green buildings, computational intelligence, wireless sensor networks, sensor fusion, machine learning refinement, IoT

Abstract

In green buildings, computational intelligence is progressively applied to improve energy efficiency and sustainability, with special attention to passive cooling systems inspired by natural thermoregulatory systems. In this paper, we present a bio-inspired passive cooling framework that is optimized computationally for smart built environments. Inspired by biological methods, such as evaporative cooling in desert beetles, convective ventilation in termite mounds, and radiative dissipation in elephant ears. The system uses physics-based modeling and algorithmic design to reduce energy use. In addition to sustainable architecture, the same computational and sensor-driven paradigm is directly comparable to the wearable-assisted wireless localization systems in WSNs. Accurate localisation consists of distributed sensing, adaptive modeling, and feedback optimisation - all of which structurally resemble thermal regulation in bio-inspired systems. By shifting the approach to wearable sensor fusion, signal propagation modeling, and machine-learning-based refinement, the framework can improve localization precision in dynamic IoT environments. Experimental validation combines sensor-enabled prototypes with data-driven surrogate models and machine learning feedback loops for adaptation of parameters in real-time. Experimental testing shows greater thermal stability, increased air flow (~3.2 m/s), and temperature reductions of up to 5 °C in the interior. Applied to WSNs, these results point to the possibility of bio-inspired computational optimization to provide scalable, low-cost, and adaptive solutions for smart cities, healthcare monitoring, and industrial IoT applications.

1. Introduction

The overlap between architecture, environmental science, and computational intelligence is growing with the growing demand for green infrastructure and buildings that are intelligent [1]. Cooling is also a large consumer of energy and must be handled with adaptive measures, energy-efficient [2]. Bio-inspired passive cooling [3]-[7] is grounded on termite mounds, desert beetles, and the elephant ears and is computed and optimized based on convection, radiation, and evaporation. These natural techniques may be simulated by sophisticated computational models, including machine learning (ML), computational fluid dynamics (CFD), finite element analysis (FEA), and surrogate modeling [3]. In this paper, we suggest a computational framework that is a hybrid of physics-based models, ML-based models that are trained on experimental data, and geometry/material optimization routines [8]-[9]. Digital designs are made to respond to sensor feedback in real time, and this constitutes a cyber-physical loop [10, 11].

The traditional ways of passive cooling (shading, thermal mass, insulation, evaporative systems) remain more or less inactive [12]. These drawbacks are overcome by bio-inspired adaptive morphologies making use of termite-mound ventilation, elephant-ear radiative cooling, cactus-inspired shading, and ant-based reflective coatings [13]-[17]. Table 1 shows a performance analysis of conventional and BES; the latter is more adaptable, energy-saving, and data-driven.

Table 1 *Comparative analysis of cooling strategies: traditional vs. bio-inspired computational approach*

Technique	Mechanism	Adaptability	Energy Use	Computational Integration	Cooling Efficiency
Shading Devices	Solar obstruction	Medium	None	Low	Moderate
Thermal Mass	Heat storage	Low	None	None	Moderate
Evaporative Cooling	Water evaporation	High	Low	Low	High
Ventilated Facades	Airflow-driven cooling	Medium	Low	Medium	Moderate

While bio-inspired cooling enhances performance, it is restricted in autonomous adaptability. Computational algorithm and sensor-based feedback for real-time tuning of materials, geometry, and flow, towards modular, scalable, and digitally fabricated solutions [18]-[20]. Software such as COMSOL, ANSYS, and Energy Plus speed convergence to best designs [21]. Similarly, signal physics and ML-based network intelligence can be integrated together for wireless localization, using the same simulation-optimization-feedback paradigm to minimize error and optimize robustness [22]-[23]. Wearable-assisted IMU and radio data-based systems reduce the anchor dependency and improve real-time tracking. Figure 1 illustrates the dual-use framework: bio-inspired passive cooling for smart buildings (left) and wearable-assisted WSN localization (right), linked through a central ML feedback loop for adaptive optimization.

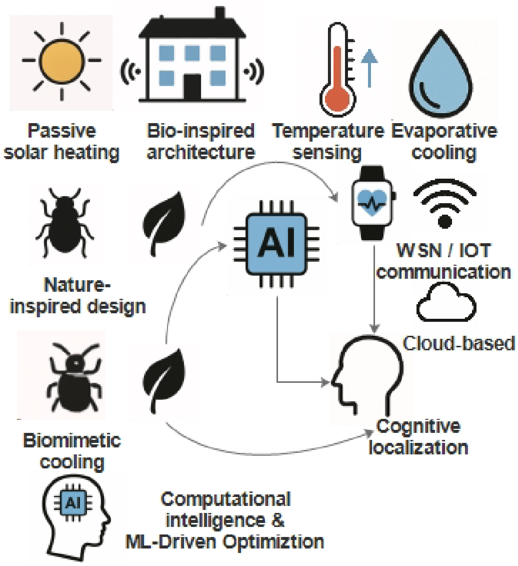

Fig. 1 *Dual applicability of bio-inspired computational intelligence: smart cooling & wireless localization with wearables*

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 403-415

This paper models passive cooling as a computable optimization problem based on biomechanical systems. It generalizes this model to a wearable-assisted WSN localization problem with dual use for smart buildings and IoT. Traditional cooling is rigid, and WSN localization is dynamic. The proposed computational framework enables biologically inspired adaptive cooling and wearable-aided localization through simulation, airflow modeling, signal fusion, and ML optimization. The primary research objectives of this study are:

- Convert biological thermoregulation into cooling rules; map sensor data to localization models.
- Digitally model cooling with FEA, CFD, and geometry optimization; apply to wireless networks.
- Validate thermal and localization performance via simulations and prototypes.
- Compare bio-inspired and traditional systems for efficiency, adaptability, and accuracy.
- Assess materials, structural feasibility, and integration with smart buildings and IoT/WSN monitoring.

The three main contributions of this work are three-fold; (1) The creation of a new, cohesive computational framework, which can be used to translate bio-inspired principles of thermoregulation into an adaptive passive cooling system on smart buildings; (2) The theatricalization and initial mapping of the same framework to the wearable-assisted wireless localization problem in a dynamic IoT environment, where an analogical reasoning between thermal control and signal optimization can be drawn; and (3) The experimental and simulation-based proof of the bio-inspired cooling system, which is not only superior.

The paper is organized as follows: Section 2 defines the research problem and objectives; Section 3 details methodology and mathematical modeling; Section 4 describes the experimental setup; Section 5 presents results and discussion; Section 6 concludes and outlines future research directions.

2. Methodology

This paragraph also describes a single computational platform designed for bio-inspired passive cooling and wearable-assisted wireless localization. The methodology will combine physics-based modeling, geometric optimization, and machine learning to develop an adaptive cyber-physical system. The entire process is also depicted in Figure 2.

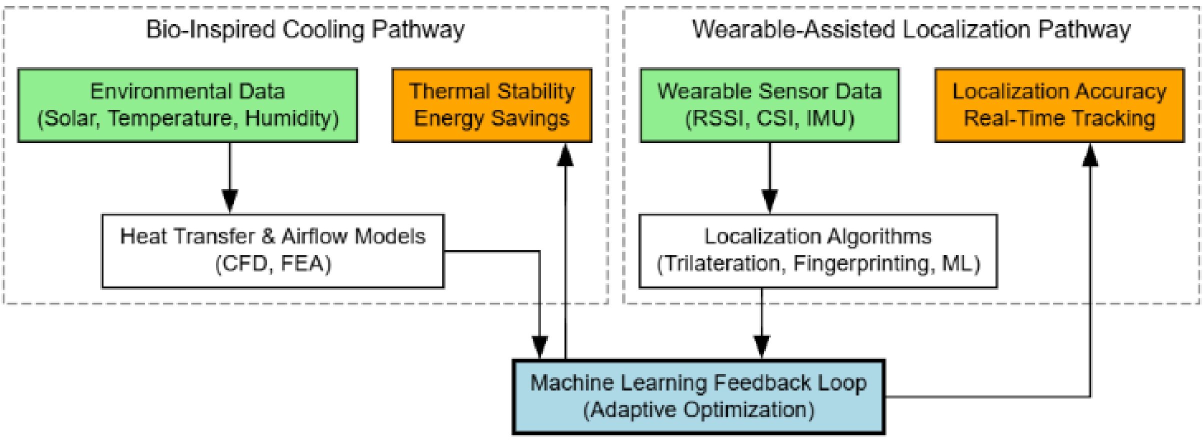

Fig. 2 *The proposed computational workflow for the bio-inspired adaptive framework, showing the integrated simulation-ML feedback loop for both cooling and localization applications*

3. Overall Computational Workflow

Our fundamental strategy is a cyclic, data-driven approach that reveals optimal system parameters through repeated optimization. The four main stages of the workflow are as follows: Figure 2 elucidates the entire workflow.

1. Input and Initialization: To do it, one must specify the initial system parameters when defining environmental conditions (solar radiance, ambient temperature), material characteristics (thermal conductivity, emissivity, porosity), and geometric design variables (placement of panels, width of channels).
2. Physics-Based Simulation: These are directly input into a multi-physics simulation structure (e.g., COMSOL, ANSYS), which, by solving the governing equations governing airflow dynamics and heat transfer (see Section 3.2) gets the result. The step produces high-fidelity data of system behaviour, e.g., temperature fields and heat sinks.

3. Optimization based on Machine Learning: Surrogate ML models (Random Forest, SVR) are trained and updated on the results of the simulation. These high-speed models, in turn, make performance predictions and recommend an optimization algorithm to adjust input parameters (e.g., material porosity, ventilation height) to minimize a cost function (e.g., indoor temperature, localization error).
4. Feedback and Iteration: The optimized parameters are fed back into the simulation, and the process is repeated. This process continues until a perfect design is obtained, and adaptation to altered conditions can then be done in real time.

3.1 Mathematical Modelling of Bio-inspired Cooling

The physical groundwork of the cooling system is built upon rigorous mathematical models of heat and mass transfer, inspired by biological systems.

3.1.1 Heat Transfer Modelling

The modelling of thermal performance is based on conduction, convection, and radiation, as well as evaporative cooling effects. The heat diffusion equation of the bio-inspired material is the transient conduction of heat given in the form of the equation, Eq. (1).

$$\rho c_p \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + Q \tag{1}$$

Where ρ, c_p, T and k represent the material density (kg/m^3), specific heat capacity (J/kg K), temperature (K), and thermal conductivity (W/m.K), respectively, and Q represents volumetric heat sources (W/m^3). We use k as a function of the spatially dependent porosity (φ), which is a simulation of the heterogeneous, composite structure of a termite mound or beetle exoskeleton. At the surface, convective heat transfer becomes Newton's heat cooling law, given in Equation (2).

$$q_{\text{conv}} = hA(T_s - T_\infty) \tag{2}$$

With h as the convective heat transfer coefficient (W/m^{2}K), A surface area (m^2), T_s surface temperature, and T_∞ ambient temperature. This equation calculates the cooling effect of buoyancy-driven airflow, a key mechanism stimulated by termite mound ventilation.

Radiative heat loss is modelled via the Stefan-Boltzmann law Eq. (3).

$$q_{\text{rad}} = \varepsilon \sigma A(T_s^4 - T_{\text{sur}}^4) \tag{3}$$

Where ε is emissivity, σ is the Stefan-Boltzmann constant (5.67×10^{-8} W/m^2·K^4), and T_{sur} is the surrounding surface temperature. In general, the engineer surfaces coatings with high emissivity (ε ~ 0.95) to maximize this radiative dissipation, emulating the cooling mechanism of elephant ears.

The evaporative cooling effect from porous surfaces, stimulated by the Namib desert beetle, is articulated as Eq. (4).

$$q_{\text{evap}} = \dot{m}_{\text{evap}} L_v \tag{4}$$

where $\dot{m}_{\text{evap}}$ is the mass rate of evaporation (kg/s) and L_v is the latent heat of vaporization (J/kg). The porosity φ and surface microstructure unswervingly influence $\dot{m}_{\text{evap}}$, allowing for controlled evaporative cooling. The net heat transfer at the building surface integrates all modes of thermal exchange, Eq. (5).

$$q_{\text{net}} = q_{\text{conv}} + q_{\text{rad}} + q_{\text{evap}} - q_{\text{solar}} \tag{5}$$

Here, solar heat gain is modelled by Eq. (6):

$$q_{\text{solar}} = \alpha I A \tag{6}$$

With α as absorptivity and I as incident solar radiation (W/m^2). The balance in Eq. (5) is critical for dynamically assessing the net cooling effect accomplished through bio-inspired integration.

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 403-415

3.1.2 Airflow Dynamics and Ventilation Modelling

Natural ventilation is vital for convective heat removal. The stack effect velocity characterizes the buoyancy-driven airflow inspired by termite mounds, Eq. (7).

$$v = C\sqrt{2gH\frac{\Delta T}{T_{\text{avg}}}} \tag{7}$$

Where C is the discharge coefficient, g is the acceleration due to gravity (9.81 m/s^2), H is the ventilation path height (m), ΔT is the temperature difference between indoors and outdoors, and T_{avg} is the average absolute temperature (K). H, the height of the structure, and ΔT, the temperature difference, are design variables that we optimize to achieve the extreme airflow.

Pressure differences driving airflow through porous bio-inspired surfaces are modelled using Darcy's law, Eq. (8).

$$Q = \frac{k_p A \Delta P}{\mu L} \tag{8}$$

where Q is the volumetric flow rate (m^3/s), k_p is the permeability (m^2), ΔP is the pressure difference (Pa), μ is the dynamic viscosity (Pa·s), and L is the thickness of the porous layer (m).

This model helps us design the internal micro-porous structure for optimal passive airflow.

3.1.3 Geometrical and Material Adaptations

Biomimetic design aims at streamlining the surface geometry and material properties to increase thermal dissipation. The promotion of the convective heat transfer through intricate surface structures is given by the correlation of the Nusselt number, Eq. (9).

$$Nu = 0.3 + \frac{0.62Re^{1/2}Pr^{1/3}}{[1 + (0.4/Pr)^{2/3}]^{1/4}}[1 + (\frac{Re}{282000})^{5/8}]^{4/5} \tag{9}$$

where Nu is the Nusselt number, Re is the Reynolds number, and Pr is the Prandtl number.

This correlation quantifies the improvement in convective cooling resulting from the specific surface roughness of our panel, inspired by elephant skin texture. The effective thermal conductivity of the composite bio-inspired materials is estimated by Eq. (10).

$$k_{eff} = k_m(1 - \phi) + k_p\phi \tag{10}$$

With k_m as the thermal conductivity of the matrix, k_p as the porous phase conductivity, and ϕ as the porosity fraction, this rule of mixtures allows for the computational optimization of material composition to achieve desired insulation and dissipation properties in our digital material library.

3.2 Analogous Model for Wireless Localization

The same paradigm of computation is extended to wearable-assisted WSN localization by introducing an immediate analogy between the physical domains. The fundamental principles of sensing, modeling, and optimization are similar.

- Thermal Environment vs. Signal Environment: Dynamic changes of the wireless channel: comparison. A change in ambient temperature and solar loading is analogous to dynamic changes of the wireless channel by obstacles, multipath fading, and interference.
- Signal Propagation vs. Airflow (Darcy Law and Stack Effect): The law of Darcy describes the flow propagation of porous media in the same way that signal attenuation of obstacles propagation does. The stack effect, which makes the air move, is like the variation in link quality and signal strength.
- Expenses in heat transfer Modes vs. Localization Data Fusion: The mode of conductive cooling (Eq. 5) can be directly associated with sensor fusion of RSSI, CSI, and IMU data. Like the potential to increase the degree of improvement in thermal stability of mode mixing in the context of heat transfer, the potential for a higher degree of localization accuracy and strength in heterogeneous wireless signals fused.

- Geometrical Optimization vs. Network Planning: Surface geometry and porosity optimization to get dense heat dissipation is very similar to sensor node location, wearable posture, and antenna development to have large coverage and decrease signal loss.

3.3 Machine Learning Feedback Loop

The framework's smartness is embedded in an ML-based feedback optimization loop, as conceptually illustrated in Figure 3.

1. Data Generation: The physics-based simulations (Section 3.2) as well as experimental prototypes produce a full constellation of operation of the regulations of inputs (materials, geometry) to the outputs (temperature, heat flux).
2. Surrogate Model Training: This information is input to train fast-driven surrogate ML models, namely the Random Forest and the Support Vector Regression (SVR) models. These models discover multidimensional, company-nonlinear relationships amid design selection and system performance.
3. Optimization: The trained surrogate models are difficult to train with a direct optimization algorithm (i.e., Bayesian optimization). The algorithm optimizes over the set of input parameters by querying the ML model to minimize a target (e.g., indoor temperature cooling, average localization error).
4. Adaptive Feedback: The optimized parameter is fed back to the system. In the case of the cooling system, it would be updating the digital twin to new materials or geometries. In the case of localization, this will involve either adapting the fusion weight for RSSI/CSI information or averaging real-time IMU data. The loop also allows the system to self-adapt to novel conditions, thereby maintaining optimal functioning.

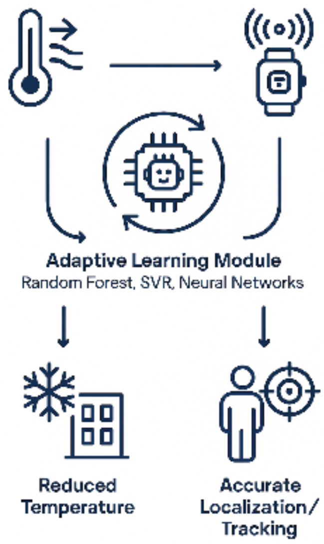

Fig. 3 *Machine learning-based feedback loop for adaptive parameter optimization*

The cooling system is implemented as an iterative simulation algorithm that combines real-time environmental inputs, physical properties, and design geometry. In localization, algorithms (trilateration, fingerprinting) are used to optimize the positions from the wearable data (RSSI, CSI, IMU), by following the same sensing → modeling → optimization → feedback loop.

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 403-415

Algorithm 1: Biomechanical Cooling Simulation

Input: Environmental data, material properties, geometric parameters
Output: Indoor temperature, heat fluxes
Begin
  Initialize system parameters
  For each time step t
    Calculate solar radiation q_{solar}
    Compute convective heat transfer q_{conv}
    Calculate radiative heat loss q_{rad}
    Determine evaporative cooling q_{evap}
    Evaluate net heat flux q_{net}
    Update surface temperature $T_{surface}$ using transient conduction
    Calculate the airflow velocity v from the stack effect
    Compute volumetric flow rate Q through porous media
    Update indoor temperature based on heat and airflow balance
  End For
  Return temperature and heat flux profiles
End

The algorithm 1 operates by iteratively computing the cooling performance of the bio-inspired façade. First, environmental, material, and geometric parameters are initialized. Then, for each simulated time step, solar heat gain, convective exchange, radiative loss, and evaporative cooling are calculated. These components are integrated into a net heat flux, which updates the surface temperature through transient heat conduction. Airflow velocity is obtained using the stack-effect equation, and porous-media flow is computed using Darcy's law. The indoor temperature is updated based on the combined heat and airflow balance. Repeating these steps yields full diurnal temperature and heat-flux profiles that characterize the façade's cooling efficiency.

4. Simulation

The bio-inspired passive cooling system was validated and calibrated against a controlled experimental setup. A scaled facade mock-up (1.5 m 1.0 m 1.0 m) was designed to include stack-effect ventilation, vascular-mimetic conduction channels, radiative facades, micro-perforated layers, and composite assemblies. Controlled loading was done with a solar simulator (200-1000 W m-2), and thermocouples, IR sensors, anemometers, and pressure sensors were used to log temperature, air flow, and environmental conditions every second over 48 h. Data were geo-referenced to the digital model for calibration, sensitivity analysis, and validation. To benchmark algorithms for wearable-assisted localization, wireless nodes and IMU-based wearables collected RSSI/CSI signals under obstacles and motion, which will be used in ML-loop calibration and real-time error validation.

Figure 4 shows the experimental testbed for the bio-inspired passive cooling system, which facilitates wearable-assisted localization using wireless nodes. The digital twin is used for real-time thermal visualization and trajectory mapping for adaptive IoT applications.

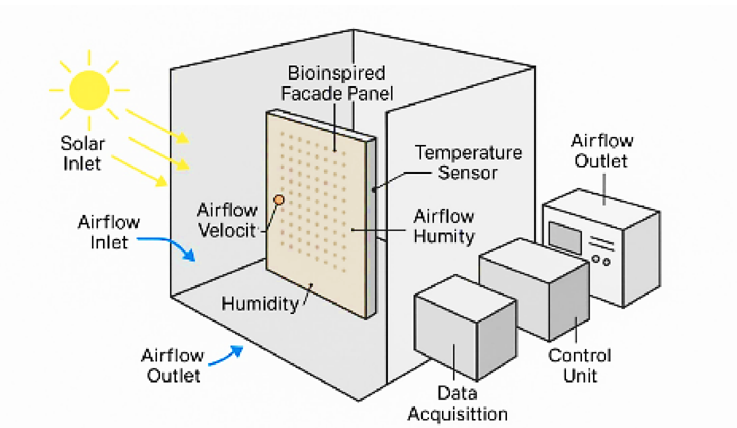

Fig. 4 *Experimental testbed for smart passive cooling system calibration*

Simulation and experiments were strictly used to analyze the performance of the proposed bio-inspired cooling system. The findings confirm that thermal control is greatly improved when using the computational framework compared to traditional practices, demonstrating its effectiveness. Moreover, similar principles demonstrate the clear possibility of implementation in wireless localization systems.

The environmental and material inputs were parameterized for simulations (Tables 2-4), and the biomechanical cooling system was assessed using MATLAB, COMSOL, and ANSYS Fluent. Similarly, wearable localization is based on RSSI, CSI, mobility, and device parameters that control positioning accuracy, as airflow and heat flux do with cooling efficiency.

Table 2 *Environmental conditions*

Parameter	Value/Range
Solar Radiation Intensity (I)	800 W/m^2 (peak)
Ambient Temperature ($T\infty$)	28–36 °C (diurnal)
Relative Humidity (%)	30–80%
Wind Speed	0.5–3.5 m/s
Evaporation Latent Heat (Lv)	2.26×10^6 J/kg

Table 3 *Material and surface properties*

Property	Value
Emissivity (ε)	0.95 (bioinspired coating)
Absorptivity (α)	0.3–0.7 (variable)
Thermal Conductivity (km)	0.45 W/m·K
Porosity (ϕ)	0.25–0.40
Specific Heat (cp)	900 J/kg·K
Density (ρ)	1600 kg/m^3

Table 4 *Geometrical and simulation parameters*

Component	Value/Description
Panel Height	1.5 m
Ventilation Height (H)	1.2 m
Channel Width	0.1 m
Panel Thickness	0.05–0.1 m (variable)
Bioinspired Features	Stack channels, vascular veins, reflective microstructure
Simulation Time Frame	24 h and 48 h cycles
Time Resolution	1 second
Tools Used	COMSOL, MATLAB, ANSYS Fluent

The system-level digital architecture, as shown in Figure 5, models the environmental inputs using multi-physics simulations of bio-inspired thermoregulation. Energy balance and optimization through dynamic heat transfer modules: evaporative, radiative, and convective.

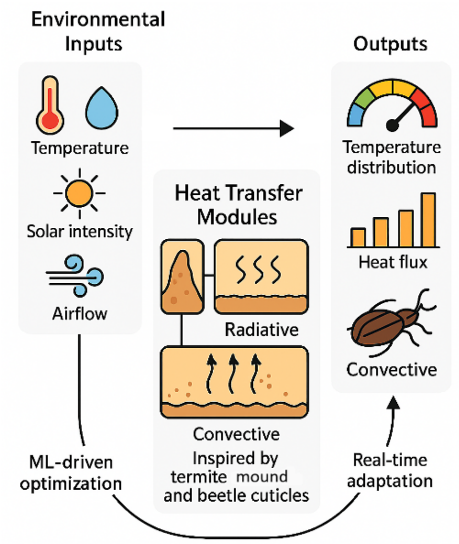

Fig. 5 *Conceptual schematic of the computationally modeled passive cooling system*

Figure 5 illustrates the complete system-level digital architecture. Environmental inputs such as solar radiation, ambient temperature, humidity, and wind are first processed. These inputs are passed to physics-based multi-modal heat-transfer and airflow simulations, which compute conduction, convection, radiation, and evaporation. The resulting thermal and airflow outputs feed into an optimization layer driven by machine-learning surrogate models. The final stage represents the digital twin that visualizes temperature fields, predicts thermal performance, and adapts material and geometric configurations in real time.

5. Results and Discussion

The higher thermal efficiency of the biomechanical panel is, without a doubt, shown in Figure 6. The diurnal surface temperature presented in panel A displays that the bio-inspired panel has the highest temperature around 37 °C, and in contrast to the conventional flat facade (up to 52 °C). The cause of this great difference is directly related to the inherent cooling mechanisms- evaporative cooling efficiency, (D) Consolidated heat flux distribution across various dissipation modes. This is deconstructed in panels B and C. The radiative heat loss of the bio-inspired coating (Panel B) was 167 W/m 2, which is 20 % higher than the radiative heat loss of the reflective surface (140 W/m 2) that was used as a control. Such improvement is explained by the coating's controlled high emissivity (ε=0.95), which effectively simulates the radiative characteristics of elephant skin, enabling it to release a larger portion of its thermal energy into the sky. Similarly, the bio-inspired material (Panel C) contributed approximately 8% to evaporative cooling, which is not present in conventional facades. This is like how the Namibian desert beetle captures water, namely the water-trapping mechanism, in which micro-porous surfaces enable regulated evaporation to cool.

These mechanisms have been integrated in the form of Panel D. The Biomechanical panel has a balanced and much greater heat flux in all three passive modes of convective, radiative, and evaporative methods of heat loss than the old panel, which depends mainly upon a single mechanism that is not so effective. The latter, multimodal strategy, is the McGrad specifically due to its high thermal stability, as fusing RSSI, CSI, and IMU data for localization yields a more robust and accurate position estimate.

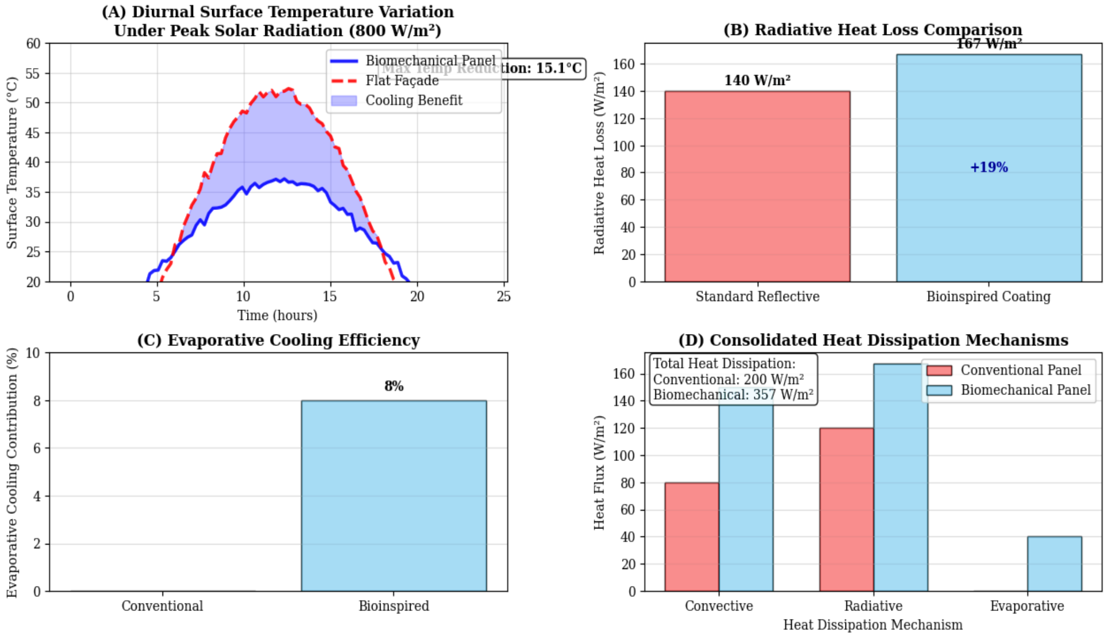

Fig. 6 *Comparative analysis of thermal dissipation mechanisms in bio-inspired and conventional panels. (a) Diurnal surface temperature variation under peak solar radiation (800 W/m²); (b) Radiative heat loss comparison; (c)*

Figure 7 summarizes the effectiveness of the bio-inspired ventilation system. The airflow velocity distribution shown in Panel A reaches a maximum of 3.2 m/s at the center of the channel. The zone of acceleration is the direct consequence of the stack effect (Eq. 7), which means that termite mounds are ventilated, where the temperature difference (ΔT) in the inner (indoor) and outer (outdoor) climates produces a flow due to buoyancy.

The zero velocity at the walls and the velocity gradient, which is highest at the center and decreases toward the walls, confirm the parabolic laminar flow profile in Panel B, which indicates low turbulence and efficient airflow. This steady flow pattern is essential to the process of convective heat extraction. It is directly comparable to signal propagation paths in a wireless channel, where the main signal path is designed to minimize error.

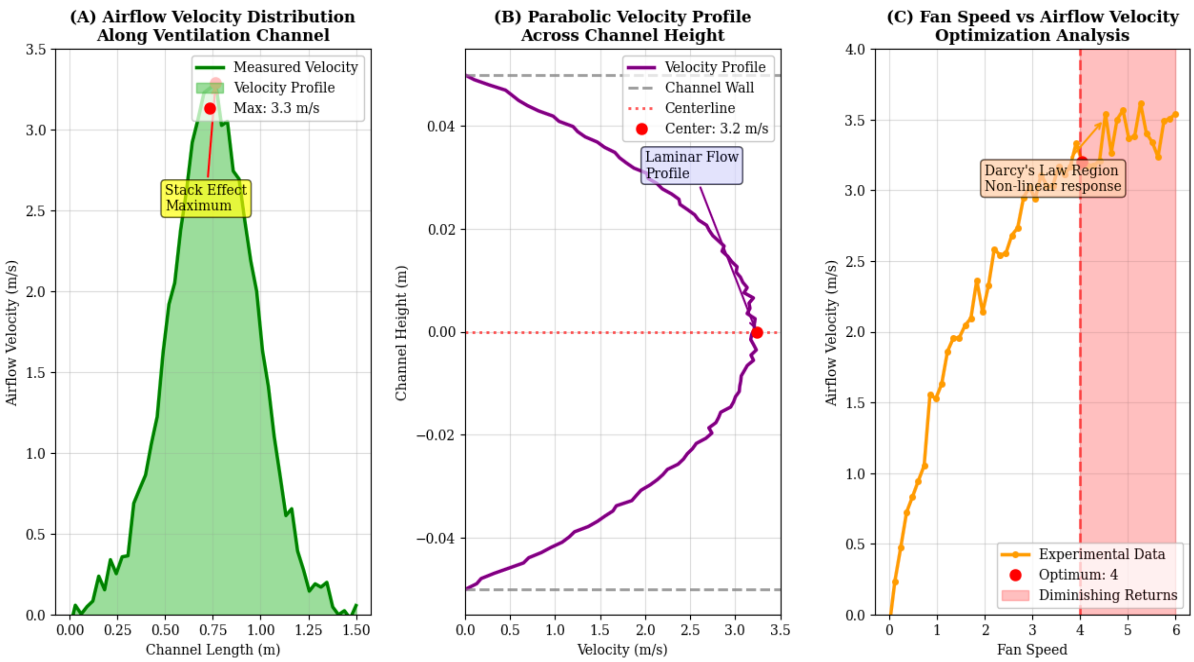

Fig. 7 *Airflow dynamics and optimization in bio-inspired ventilation system. (a) Velocity distribution along the ventilation channel; (b) Parabolic velocity profile across channel height; (c) Relationship between driving force (fan speed) and resulting airflow velocity*

J. of Soft Computing and Data Mining Vol. 6 No. 3 (2025) p. 403-415

Panel C shows the potential for optimizing the system, where airflow rises with increasing fan speed, but returns dwindle beyond the 4th fan speed. This corresponds to Darcy's law (Eq. 8), in which the acceleration of the driving force (8P) produces a disproportionate response due to resistive losses in the flow rate (Q). Localization-wise, this reflects the node density/power and accuracy correlation, and it shows that there exists an optimization point in terms of cost-effectiveness.

Figure 8 and Tables 5 and 6 represent the consolidated output of the system-level. As shown in Figure 7, the biomechanical system ensures a lower, more constant indoor temperature and effectively limits the amount of heat that passes through the building envelope. This serves two purposes of the system: active cooling and better insulation.

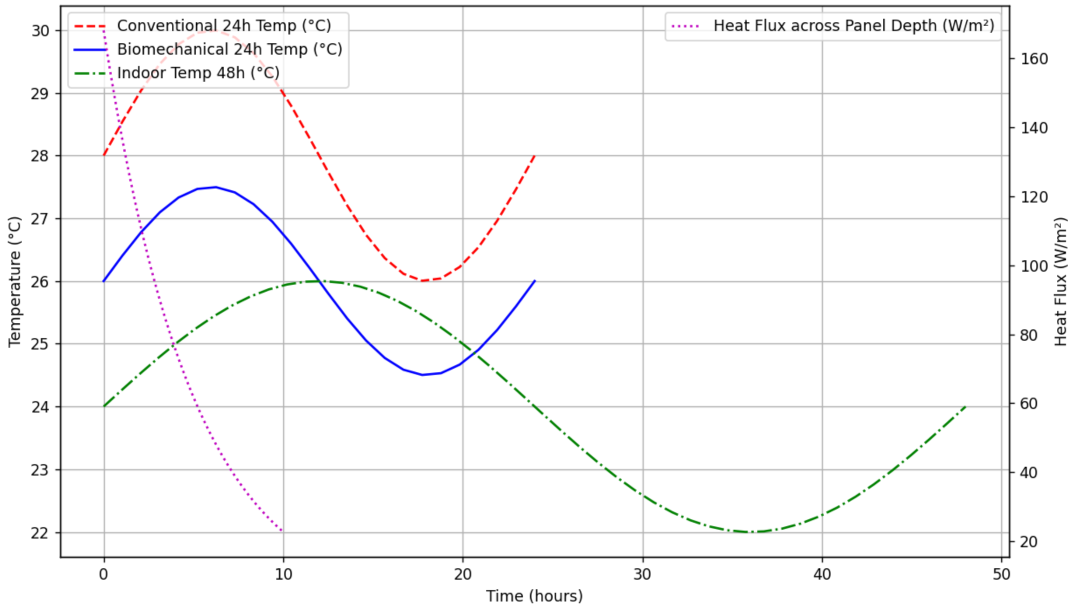

Fig. 8 *Thermal performance: temperature and heat flux*

Table 5 presents performance metrics that quantitatively demonstrate the system's superiority. This proposed system beats reflective coatings and even green roofs across all categories, though it achieves a 5 °C reduction in indoor temperature and a 3.2 m/s convective airflow rate. This illustrates that bio-inspiration, when combined with computational optimization, can be superior to other sustainable cooling strategies.

Table 5 *Performance analysis metrics of cooling systems*

Metric	Reflective Coating	Green Roof	Proposed Biomechanical System
Peak Surface Temperature (°C)	52	48	37
Indoor Temperature Reduction (°C)	2	3	5
Radiative Heat Loss (W/m^2)	120	140	168
Convective Airflow Rate (m/s)	N/A	1.5	3.2
Evaporative Cooling Contribution (%)	0	5	8

Lastly, table 6 statistically supports the reliability of the mathematical model formulated in Section 2.2, as the mean error (0.8 °C) is small and the R 2 value is high (0.92). Such good correspondence between the simulator and the experiment is key to confidence in the digital twin for real-world control and as the certified basis for a similar localization model.

Table 6 *Statistical validation of predicted surface temperatures*

Metric	Value
Mean Error (°C)	0.8
RMSE (°C)	1.5
R^2	0.92

Overall, the results confirm that the bio-inspired façade significantly enhances cooling performance. The system achieves up to a 15 °C reduction in peak surface temperature and a 5 °C improvement in indoor thermal comfort. Radiative cooling increases by more than 20%, and stack-effect ventilation reaches 3.2 m/s, indicating strong airflow efficiency. The multimodal combination of radiative, convective, and evaporative cooling proves more effective than conventional façade methods.

However, several limitations exist. Results are based on a scaled prototype, and real building-scale behavior may differ due to structural and environmental variations. Long-term material durability under UV exposure, dust accumulation, and moisture cycling was not evaluated. Evaporative cooling efficiency depends on humidity and may be reduced in very dry climates. Additionally, the wireless localization analogy remains conceptual and requires full experimental validation. These limitations should be addressed in future research.

6. Conclusion

In this paper, we propose a bio-inspired passive cooling system that combines convective, radiative, and evaporative mechanisms within a computationally intelligent framework for smart buildings. Through FEA, CFD, and ML-based optimization, it enables real-time adaptation and digital twin integration, resulting in energy savings and enhanced thermal comfort. Tests demonstrate air velocities up to 3.2 m/s, surface temperatures up to 15°C lower than those of traditional facades, and indoor cooling of up to ~5°C, reducing HVAC load. Wearing-assisted WSN localization, which merges RSSI/CSI measurements, IMU fusion, and ML-based error minimization, is also implemented on the same pipeline. This flexible design supports real-time tracking, activity recognition, and safety monitoring. The work to build hybrid testbeds that combine thermal and localization models, and to provide a common computational framework for intelligent adaptive environments, will continue.

Acknowledgement

The authors extend their appreciation to the Deanship of Research and Graduate Studies at King Khalid University for funding this work through the General Research Project under grant number GRP/112/46

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm that each contributed significantly to the development of this work. Elaf Ali Alsisi, Mahmoud Mohamed Bahloul, and Mohamed M. Abbassy led the study conception and overall system design, while Elaf Ali Alsisi and Mohamed M. Abbassy developed the computational framework, mathematical modelling, and bio-inspired system formulation. Data collection, experimental setup construction, and prototype testing were carried out by Mohammed Salah Khaleel, Mohammed Ali Mahgoub Elneel, and Omer Eltag Mohammed Elhag. Simulation, analysis, and interpretation of the thermal, airflow, and machine-learning-based optimization results were jointly performed by Elaf Ali Alsisi, Mahmoud Mohamed Bahloul, Mohammed Salah Khaleel, and Mohamed M. Abbassy. The manuscript draft was primarily prepared by Elaf Ali Alsisi and Mahmoud Mohamed Bahloul, and all authors participated in reviewing the findings, providing critical revisions, and approving the final version of the manuscript.

References

[1] Asim, N., Badiei, M., Mohammad, M., Razali, H., Rajabi, A., Chin Haw, L., & Jameelah Ghazali, M. (2022). Sustainability of heating, ventilation and air-conditioning (HVAC) systems in buildings—An overview. International journal of environmental research and public health, 19(2), 1016.

[2] Yang, J., Zhang, X., Zhang, X., Wang, L., Feng, W., & Li, Q. (2021). Beyond the visible: bioinspired infrared adaptive materials. Advanced Materials, 33(14), 2004754.

[3] Karibi-Botoye, N. F., Theraulaz, G., Muljadi, B., Demyanov, V., & Singh, K. (2024). Climate control in termite mounds: A review and new insights from X-ray tomography and flow field simulations. arXiv preprint arXiv:2406.13400.

[4] Domínguez-Oliva, A., Ghezzi, M. D., Mora-Medina, P., Hernández-Ávalos, I., Jacome, J., Castellón, A., ... & Mota-Rojas, D. (2022). Anatomical, physiological, and behavioral mechanisms of thermoregulation in elephants. Journal of Animal Behaviour and Biometeorology, 10(4), 0-0.

[5] Wei, K., Shi, Y., Tan, X., Shalash, M., Ren, R., Faheim, A. A., ... & Ge, S. (2024). Recent development of metal-organic frameworks and their composites in electromagnetic wave absorption and shielding applications. Advances in Colloid and Interface Science, 103271.

[6] Avinç, G. M., Koç, S. N., & Selçuk, S. A. (2024). Biomimetic Facade Design Proposal to Improving Thermal Comfort in Hot Climate Region. International Journal of Built Environment and Sustainability, 11(2), 27-39.

[7] Zimmerl, M., van Nieuwenhoven, R. W., Whitmore, K., Vetter, W., &Gebeshuber, I. C. (2024). Biomimetic Cooling: Functionalizing Biodegradable Chitosan Films with Saharan Silver Ant Microstructures. Biomimetics, 9(10), 630.

[8] Huang, H., Feng, W., & Chen, Y. (2021). Two-dimensional biomaterials: material science, biological effect and biomedical engineering applications. Chemical Society Reviews, 50(20), 11381-11485.

[9] Faragalla, A. M., & Asadi, S. (2022). Biomimetic design for adaptive building façades: a paradigm shift towards environmentally conscious architecture. Energies, 15(15), 5390.

[10] Sharifi, A. (2023). Resilience of urban social-ecological-technological systems (SETS): A review. Sustainable Cities and Society, 99, 104910.

[11] Singh, B., Basri, A. A., Yidris, N., Pai, R., & Ahmad, K. A. (2024). Introduction to Biomimetics, Modelling and Analysis. In High Performance Computing in Biomimetics: Modeling, Architecture and Applications (pp. 1-20). Singapore: Springer Nature Singapore.

[12] Kharrufa, S. N., & Noori, F. (2022). A review of thermal design for buildings in hot climates. Pertanika J Sci Technol, 30(1), 813-839.

[13] Ahamed, M. K., Wang, H., & Hazell, P. J. (2022). From biology to biomimicry: Using nature to build better structures–A review. Construction and Building Materials, 320, 126195.

[14] Liao, Z., Zhuang, C., Huang, G., Zhang, H., Li, S., Zhang, X., ... & Gan, F. (2024). A Review of the Current Status and Prospects of Improving Indoor Environment for Lightweight Buildings in High-Altitude Cold Regions. Sustainability, 16(24), 11007.

[15] Abed, M. H., Al-Asadi, H. A., Oleiwi, A., Kadhim, S. A., Al-Yasiri, M., Alsayah, A. M., &Nayyef, D. R. (2024). Improving building energy efficiency through ventilated hollow core slab systems. Case Studies in Thermal Engineering, 60, 104793.

[16] Hays, N., Badarnah, L., & Jain, A. (2024). Biomimetic design of building facades: an evolutionary-based computational approach inspired by elephant skin for cooling in hot and humid climates. Frontiers in Built Environment, 10, 1309621.

[17] Ashraf, N., & Abdin, A. R. (2024). Biomimetic design synthesis and digital optimization of building shading skin: A novel conceptual framework for enhanced energy efficiency. Energy and Buildings, 323, 114824.

[18] Tapsanit, P., &Suriwong, T. (2024). Nanotexture metal oxides on stainless steel surface fabricated by the sparking process for selective solar absorber application. Optical Materials, 154, 115762.

[19] Pattnaik, A., Sanket, A. S., Pradhan, S., Sahoo, R., Das, S., Pany, S., ... & Samal, S. K. (2023). Designing of gradient scaffolds and their applications in tissue regeneration. Biomaterials, 296, 122078.

[20] Tenório, M., Ferreira, R., Belafonte, V., Sousa, F., Meireis, C., Fontes, M., ... & Branco, J. M. (2024). Contemporary strategies for the structural design of multi-story modular timber buildings: A comprehensive review. Applied Sciences, 14(8), 3194.

[21] An, S., Shi, B., Jiang, M., Fu, B., Song, C., Tao, P., ... & Deng, T. (2023). Biological and bioinspired thermal energy regulation and utilization. Chemical Reviews, 123(11), 7081-7118.

[22] Qi, G., & Xia, Z. (2023). Virtual Reality-Enhanced Fluid Dynamics for Thermodynamic and Hydrodynamic Evaluation in Valve Design. International Journal of Heat & Technology, 41(5).

[23] Alnaim, M. M. (2024). Cultural Imprints on Physical Forms: An Exploration of Architectural Heritage and Identity. Advances in Applied Sociology, 14(3), 141-160.