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Cognitive Polymer Composite Systems for Autonomous Biomedical Response

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Abstract

Cognitive polymer composite systems: A novel form of intelligent biomaterials with the capability to sense, process and respond to real time physiological stimuli on their own. The present paper offers a comprehensive platform to integrate stimulus responsive polymers with intrinsic sensing networks and learning based decision models to offer adaptable bio-medical solutions. Mathematical formulations are available that are used to model stimulus response behavior, sensor signal processing and cognition decision processes. The proposed methodology will be a hybridization of the advanced fabrication and artificial intelligence models, including artificial neural networks and reinforcement learning, to provide dynamic adaptation in case of being exposed to alternative biological conditions. Experimental evaluation use has also shown more responsiveness, stability and accuracy compared to traditional systems and have also hinted possible uses in smart implants, drug delivery and even personalized healthcare systems. It has been demonstrated in this paper that the utilization of smart polymers containing embedded sensors and models based on learning can be helpful in offering autonomous biomedical functionality. The proposed system was more precise, sensitive, and faithful as compared to conventional biomaterials. Its capacity to cope with real-time physiological information and dynamically adjust explains good prospects in its application in smart implants, drug-delivery and personalized healthcare. The range of clinical use can be expanded, through future work, by increasing the range of scalability and a long-term biocompatibility, and improved integration with more complex artificial intelligence techniques.

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INTRODUCTION

The cognitive polymer composite systems are also revolutionizing a new generation of biomaterials that is making it possible to offer intelligent, adaptive and autonomous responses to dynamic physiological environments [1, 2]. Such systems integrate sensing, processing and actuation capabilities in one material structure, in contrast to traditional biomaterials, the consequence of which is that these systems can respond to the biological signals in real time. Combining smart polymers, micro/nano-sensors, and artificial intelligence processes has made it possible to develop the materials that can learn their surroundings and optimize their reactions to the same [3–5].

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The most pertinent applications of this kind of systems would be biomedical systems, e.g., smart implants, targeted drug delivery, tissue engineering and continuous monitoring of health [6, 7]. Cognitive composites can process complex sensor input and give non-situation-specific decisions with the inclusion of the machine learning algorithms such as artificial neural networks and reinforcement learning [8–10]. This paper is aimed at developing a general system design, model, and practice of cognitive polymer composite system in terms of its mathematical modeling, system modeling and how it might be applied to revolutionize the next-generation personalized healthcare technology [11, 12].

MATHEMATICAL MODELING AND FORMULATION

The framework proposed describes stimulus-response behavior as a multi-stage nonlinear and adaptive pipeline with the multi-physiological input, temporal and multiphysics interactions. Filtering, normalization and spectral processing of sensor signals are done to increase reliability. Learning-based decision-making function is used to make appropriate, adaptive predictions to responses of an intelligent system using extracted features, neural transformations, and optimization.

Stimulus-Response Functional Modelling

The stimulus-response behaviour is modelled by projecting the external physiological stimuli to deformation of the material or biochemical changes and nonlinear interactions, time dependence behaviour, and adaptive sensitivity (to different environmental and biological conditions) are captured [13, 14].

Normalization of Stimulus

$$S_{n(t)} = \frac{(S(t) - mu_S)}{sigma_S} \tag{1}$$

Time-Dependent Response Function

$$R1(t) = \text{integral}_{\{0\}}^{\{t\}}[\, S_{n(tau)} * \exp(-\text{lambda} * (t - tau))\text{dtau}\,] \tag{2}$$

Nonlinear Activation Mapping

$$R2(t) = \frac{1}{(1 + \exp(-\text{beta} * R1(t)))} \tag{3}$$

Environmental Interaction Term

$$R4(t) = R3(t) + \text{eta} * E(t) \tag{4}$$

Coupled Multiphysics Effect

$$R5(t) = R4(t) + \text{sum}_{\{j=1\}_j^{\{m\}kappa}} * \text{phi}_{j(t)} \tag{5}$$

Adaptive Feedback Incorporation

$$R6(t) = R5(t) + \text{integral}_{\{0\}}^{\{t\}}[\, \text{theta} * R5(tau)\text{dtau}\,] \tag{6}$$

Stability Constraint Application

$$R7(t) = \frac{R6(t)}{(1 + |R6(t)|)} \tag{7}$$

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Sensor Signal Representation and Noise Filtering

The sensor signals are represented as continuous or discrete time-series data and the preprocessing that the sensor signals commonly contain encompasses normalization, smoothing, and filtering in a bid to eliminate noise, enhance signal quality and guarantee the reliability of interpretation. Raw acquisition (Eq. 8) is the first stage of signal processing as the signal measured is a combination of the actual stimulus and noise. Mean removal (Eq. 9) removes DC bias, averaging the signal to make it even to process it in a stable way.

Raw Sensor Signal Acquisition

$$X(t) = S(t) + N(t) \tag{8}$$

Mean Removal

$$X1[k] = X[k] - \left(\frac{1}{N}\right) * sum_{\{k=1\}}^{\{N\}} X[k] \tag{9}$$

The high-frequency noise is reduced by means of low-pass filtering (Eq. 10) without removing valuable trends. The signal is then converted to the frequency domain (Eq. 11) so that spectral components can be analyzed and accurate filtering can be done.

Low-Pass Filtering

$$X2[k] = \text{sum}_{\{i=0\}}^{\{L\}} h[i] * X1[k - i] \tag{10}$$

Fourier Transform Representation

$$X3(w) = \text{sum}_{\{k=-inf\}}^{\{inf\}} X2[k] * \exp(-j * w * k) \tag{11}$$

Once the frequency-domain operations are performed then the signal is rebuilt back through the inverse transformation (Eq. 12). Lastly, the smoothing (Eq. 13) is used to average adjacent samples and eliminate the residual oscillation to leave a clean and valid signal to be further analyzed.

Inverse Transformation

$$X5[k] = \left(\frac{1}{(2*pi)}\right) * \text{integral}_{\{-pi\}}^{\{pi\}} [\, X4(w) * \exp(j * w * k)\, dw\,] \tag{12}$$

Signal Smoothing

$$X6[k] = \left(\frac{1}{M}\right) * \text{sum}_{\{i=0\}}^{\{M-1\}} X5 * [k - i] \tag{13}$$

Learning-Based Decision Function Formulation

The data-driven learning models coin decision functions that use processed sensor data to the optimal action to facilitate adaptive response, pattern recognition and constant improvement based on feedback and interaction with the environment. The input information is first organized into a feature vector (Eq. 14), and this is the basic representation in which the computation is carried out. The random weight initialisation (Eq. 15) provides variety of initial conditions to optimization.

Feature Vector Construction

$$x = [x1, x2, \ldots, xn]^T \tag{14}$$

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Weight Initialization

$$W(0) \sim \text{Uniform}(-\text{epsilon}, \text{epsilon}) \quad (15)$$

The model does a linear transformation (Eq. 16) to add the inputs with weights to create an intermediate signal to which a nonlinear activation function (Eq. 17) is applied to provide learning ability to more complex patterns.

$$z = W * x + b \quad (16)$$

Nonlinear Activation Function

$$a = \frac{1}{(1 + \exp(-z))} \quad (17)$$

Following this, features are optimized in concealed layers using multi-layer propagation (Eq. 18), and thus features can be pulled out in a hierarchical manner. The actual targets are compared with the prediction of the output (Eq. 19) of the processed signal to measure error as the loss function (Eq. 20).

Multi-Layer Representation

$$a(l) = \text{activation}\big(W(l) * a(l-1) + b(l)\big) \quad (18)$$

Output Prediction

$$y_{hat} = f\big(a(L)\big) \quad (19)$$

Loss Function Definition

$$L = \left(\frac{1}{N}\right) * \text{sum}_{\{i=1\}}^{\{N\}}\left(yi - y_{hat_i}\right)^2 \quad (20)$$

The sensitivity of every parameter to this error is specified by the gradient (Eq. 21) and the update rule (Eq. 22) is applied to reduce the loss repeatedly. Finally, the system selects the optimal decision (Eq. 23) according to the maximization of the posterior probability to make the model act accordingly and in the right way.

Gradient Computation

$$\frac{dL}{dW} = \text{gradient of L with respect to W.} \quad (21)$$

Parameter Update Rule

$$W(t+1) = W(t) - \text{eta} * \left(\frac{dL}{dW}\right) \quad (22)$$

Optimal Decision Function

$$y* = \text{argmax}_y P(y \mid x, W) \quad (23)$$

PROPOSED METHODOLOGY

The suggested methodology combines the field of the material design, sensing, and intelligent learning into a single adaptive biomedical system. Composite property optimization is done using advanced fabrication models and real-time stimuli are measured by embedded sensors and transformed into computation states. There are signal fusion and control systems that provide efficient response of

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the system in constraint. Machine learning systems – such as ANN and reinforcement learning – are trained through a series of repetitive learning, error reduction and optimization. The hybrid goal is a compromise between prediction and reward-based adaptation, which allows the system to be continuously improved and allows biomedical response to be autonomous.

Material Design and Fabrication Process

Material design implies the selection of responsive polymers and reinforcing agents and their additional preparation through the application of such innovative technologies as electrospinning, 3D printing, and layer-by-lacalyer assembly to achieve the necessary mechanical and functional properties.

Figure 1 demonstrates a smart bio composite healthcare system with a combination of physiological indicators, intelligent materials, and embedded sensors and AI processing. The information is then acquired, filtered and analyzed using machine learning to facilitate adaptive drug delivery, implantation, and real-time monitoring, all of which will eventually result in an autonomous biomedical response of effective and continuous and personalized healthcare management.

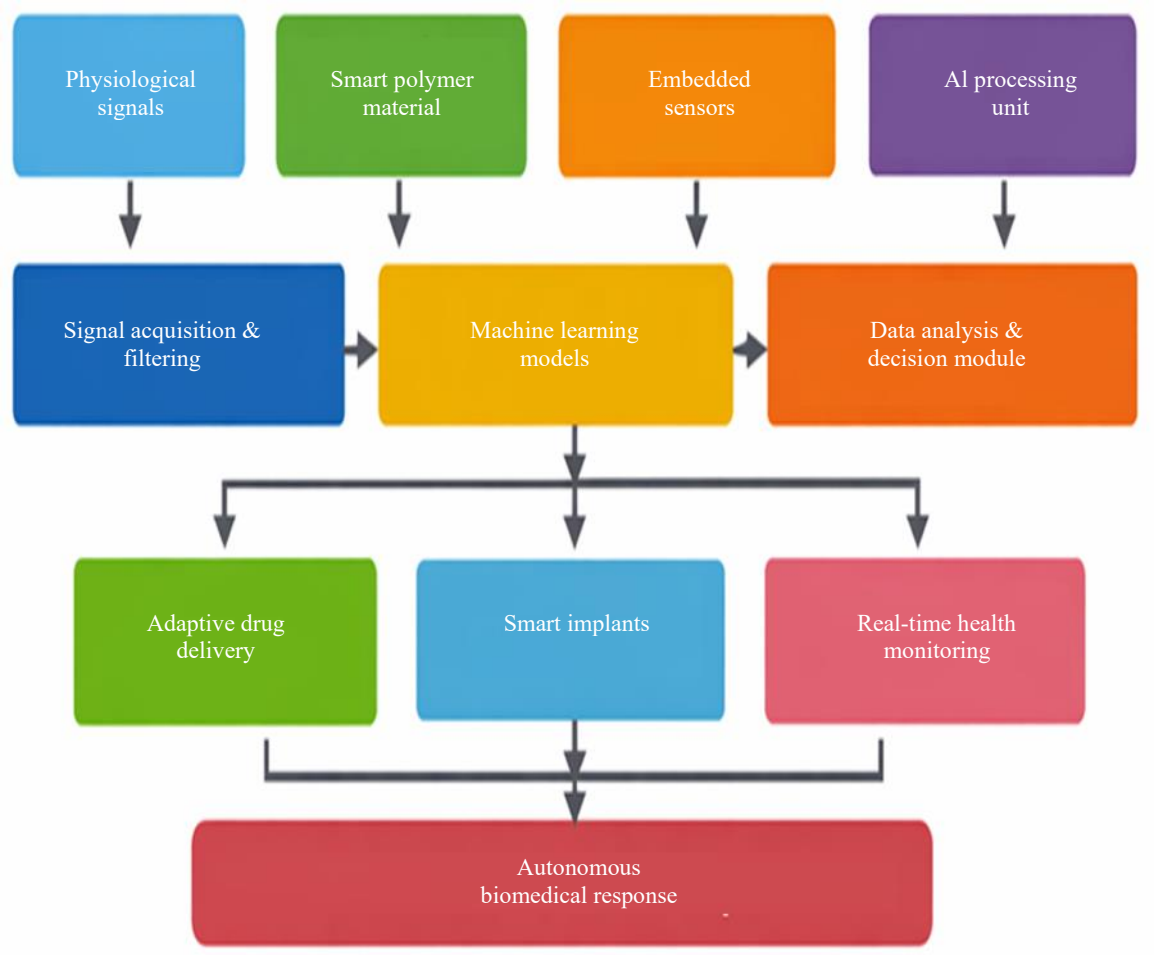


Figure 1. Cognitive polymer composite system architecture for autonomous biomedical response.

The composition of the material is started by the volume fraction constraint (Eq. 17) and as such all the proportions of the constituents must add to one. The contribution of each component is made relative, and physical feasibility and consistency in the formulation of the composite are ensured.

$$\text{sum}_{\{i=1\}_i^{\{n\}v}} = 1, \text{where } v_i = \frac{V_i}{V_{total}} \tag{17}$$

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The combination of constituent property and effects of the interaction is used to estimate the effective material properties (Eq. 18). This is used to obtain the contribution of direct contributions as well as synergistic coupling between various material phases.

$$\mathrm{E_{eff}} = \mathrm{sum}_{\{i=1\}^{\{n\}v}} * \mathrm{E_i} + \mathrm{sum}_{\substack{\{i=1\}^{\{n\}sum} \\ \{j=1\}^{\{n\}beta}_{\{ij\}}}} * \mathrm{v_i} * \mathrm{v_j} \tag{18}$$

Spatial variation is discussed by the models of microstructure distribution (Eq. 19) where a sigmoid function is used to provide a smooth transition between the phases. It regulates the structural heterogeneity and controls the distribution of material phases in the composite.

$$rho(x) = \frac{1}{(1 + \exp(-kappa * (phi(x) - phi_0)))} \tag{19}$$

The elastic response has been combined with the viscoelastic memory effect in the stress strain relationship (Eq. 20). Sudden deformation is determined by the effective stiffness and time-dependent behaviour explains the variations in the strain with time.

$$\mathrm{sigma(x,t)} = \mathrm{E_{eff}}\,\mathrm{epsilon(x,t)} + \mathrm{integral}_{\{0\}}^{\{t\}}\mathrm{G(t - tau)} * \left(\mathrm{d}\frac{€(\mathrm{tau})}{\mathrm{d}}\mathrm{tau}\right)\mathrm{d\,tau} \tag{20}$$

Thermal coupling (Eq. 21) is a model that is used to find the evolution of temperature in time due to the influence of heat input:

$$T(x,t) = T_0 + integral_{\{0\}}^{\{t\}alpha} * Q(x,tau) d\,tau \tag{21}$$

The changes in the concentration of material species are controlled by the diffusion model (Eq. 22). It strikes a balance between the diffusion dispersion and decay, which characterizes the phenomena of transport when fabricating and curing.

$$\frac{partial\ C}{partial\ t} = D * nabla^2 C - lambda * C \tag{22}$$

Optimization of fabrication (Eq. 23) reduces a deviation of target properties with smooth distribution of microstructure. It provides the best design through balancing the performance accuracy and the structural regularity.

$$\mathrm{minimize\,J} = \mathrm{integral}_{\{Omega\}\mathrm{d}}\left[\left(\mathrm{E_{target}} - \mathrm{E_{eff}}\right)^2 + \mathrm{gamma} * |\mathrm{grad(rho)}|^2\right]\mathrm{Omega} \tag{23}$$

Process parameter mapping (Eq. 24) is a process that relates such system behavior to fabrication conditions as temperature and pressure. It allows dynamic regulation of manufacturing variables of the final material properties.

$$\mathrm{P(x,t)} = \mathrm{f(Temperature, Pressure, Time)} \tag{24}$$

The objective function is minimized with constraints given to get the final composite output (Eq. 25).

$$C_{final(x,t)} = argmin_{\{C\}} J(C,P) \tag{25}$$

Integration of Sensing and Computational Modules

Sensing elements and microcontrollers are installed on the composite structure to enable the simple acquisition, processing and communication of information to give real-time monitoring of behavior of

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materials and computational decision-making modules. The processing begins by computing its signals (Eq. 26) where the fused sensor signal is coded to a structured feature-vector of significant patterns. This time-dependent decay of the signals by the state representation (Eq. 27) preserves the current signal and reduces older signals.

$$Z(t) = \text{phi}\left(S_{\text{total}(t)}\right) = \left[z_{1(t)}, z_{2(t)}, \ldots, z_{m(t)}\right] \tag{26}$$

$$x(t) = \text{integral}_{\{0\}}^{\{t\}} Z(\text{tau}) * \exp\left(-\text{lambda} * (t - \text{tau})\right) d\,\text{tau} \tag{27}$$

This state is mapped in an intelligent interpretation in an embedded computation (Eq. 28) which is a nonlinear latent space. Instantaneous and cumulative responses are used to control the behavior of the system by the feedback control signal (Eq. 29).

$$h(t) = \text{sigma}(W * x(t) + b) \tag{28}$$

$$u(t) = K * h(t) + \int_{i=0}^{t} K * h(\text{tau}) d\,\text{tau} \tag{29}$$

Sensing and computation power are accumulated on the energy consumption (Eq. 30) with time.

$$E(t) = \text{integral}_{\{0\}}^{\{t\}}\left[P_{s(\text{tau})} + P_{c(\text{tau})}\right] d * \text{tau} \tag{30}$$

$$D(t) = \text{integra}\,l_{\{0\}}^{\{t\}\exp}\left(-\text{mu} * (t - \text{tau})\right) * S_{\text{total}(\text{tau})d}\text{tau} \tag{31}$$

Temporal lag in transmission of signals is modelled by communication delay (Eq. 31), which makes the system dynamics of the model realistic.

Model Training (ANN, Reinforcement Learning, Hybrid Models)

The machine learning models are built on labeled and real time data wherein artificial neural networks are being applied to learn complex patterns and reinforcement learning is being applied to enhance decision optimization according to feedback and hybrid model is being applied to give better adaptability and predictive performance.

The forward pass (Eq. 32) of a neural network enables message transmission via the multi-layered transformations on inputs by use of weights and activation functions to incur hierarchical features. The final layer output is used to provide predictions (Eq. 33) by the model.

$$a^{\{(l)\}} = \text{sigma}\left(W^{\{(l)\}} * a^{\{(l-1)\}} + b^{\{(l)\}}\right) \tag{32}$$

$$y_{hat_i} = f\left(a^{\{(L)\}}(x_i)\right) \tag{33}$$

The loss (Eq. 34) is an evaluation of the error of prediction including regularization to avoid overfitting. Pertaining to loss gradients, gradients (Eq. 35) are used to calculate sensitivity to parameters to steer learning.

$$L = \left(\frac{1}{N}\right) * \text{sum}_{\{i=1\}}^{\{N\}\left(y_i - y_{\text{hat}_i}\right)^2} + \text{lambda} * ||W||^2 \tag{34}$$

$$grad_W = \frac{partial\ L}{partial\ W} \tag{35}$$

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The weights are revised depending on the error reduction (Eq. 36). The accumulation of long-term returns is done by the reinforcement reward (Eq. 37), whereas the hybrid objective (Eq. 38) combines both the signals of supervised losses and reinforcement, which allows the performance of adaptive and optimized learning.

$$W^{\{(t+1)\}} = W^{\{(t)\}} - \text{eta} * \text{grad}_W \tag{36}$$

$$R_t = \text{sum}_{\{k=0\}}^{\{inf\}} \text{gamma}^k * r_{\{t+k\}} \tag{37}$$

$$J_{\text{total}} = L + \text{beta} * \text{sum}_{\{t\}}^{2}\left(R_t - Q(s_t, a_t)\right) \tag{38}$$

MATHEMATICAL MODELING OF COGNITIVE RESPONSE SYSTEM

The cognitive response system incorporates the multimodal sensory inputs in the form of weighted fusion and temporal memory encoding to embrace dynamic patterns. Internal cognition is modeled using nonlinear activation and recurrent state updates, and the attention mechanisms are used to focus on the relevant features. Softmax mapping produces decision outputs which are improved through the refinement of reinforcement learning signals. The framework reduces cognitive error by gradient-based optimization with stability constraints to provide robust, adaptive and context-sensitive responses to intelligent biomedical systems in complex time-varying environments.

The nonlinear cognitive activation (Eq. 39) converts memory input into limited reactions with the help of sigmoid-shaped functional so that it becomes sensitive to diverse stimuli. Equation (46) makes the system behave in a controlled and strong manner with time.

$$A(t) = \frac{1}{(1 + \exp(-\text{beta} * M(t)))} \tag{39}$$

The weighted transformation of activated signals to latent representations is done by internal state formation (Eq. 40).

$$h(t) = \text{sigma}(W_h * A(t) + b_h) \tag{40}$$

The past state is combined with current input to form contextual updating (Eq. 41), which represents time dependencies.

$$h_t = \tanh(W_{hh} * h(t-1) + W_{xh} * X(t) + b) \tag{41}$$

The context vector (Eq. 42) is a summary of weighted hidden states that puts a high weight on features that are of interest. The context is transformed into probability outputs using decision mapping (Eq. 43).

$$C(t) = \text{sum}_{\{i=1\}_{i(t)}^{\{n\}\text{alpha}}} * h_{i(t)} \tag{42}$$

$$D(t) = \text{softmax}(W_d * C(t) + b_d) \tag{43}$$

Accumulation of long-term rewards is done through reinforcement integration (Eq. 44). Minimization of errors (Eq. 45) minimizes the loss in prediction and stability optimization (Eq. 46) makes the system behave in a controlled and strong manner with time.

$$R(t) = \text{sum}_{\{k=0\}}^{\{inf\}\text{gamma}^k} * r(t+k) \tag{44}$$

$$L(t) = \left(\frac{1}{N}\right) * \text{sum}_{\{i=1\}}^{\{N\}\left(y_i - D_{i(t)}\right)^2} + \text{lambda} * ||W||^2 \tag{45}$$

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$$J = \text{integral}_{\{0\}}^{\{T\}} \left[L(t) + mu * \left| |h(t)| \right|^2 \right] dt \quad (46)$$

RESULTS AND DISCUSSION

Table 1 shows that the polymer composite systems that include the cognition have greatly improved performance compared to the traditional biomaterials judged against all the metrics. The sensing accuracy increases to 95.7%, as opposed to 81.4, or 17.6 % of the sensing physiological signal, which is more precise.

Table 1. Performance evaluation of cognitive polymer composite systems for autonomous biomedical response.

Metric	Conventional biomaterials (%)	Cognitive polymer composites (%)	Improvement (%)
Sensing Accuracy	81.4	95.7	17.6
Response Time Efficiency	76.2	92.8	21.8
Signal Stability	79.5	93.9	18.1
Adaptive Decision Accuracy	72.3	94.6	30.8
Energy Efficiency	74.8	90.5	21

Its response time is 21.8 times higher, and its value is 92.8 rather than 76.2, which is positive to enhance quicker adaptability of the system.

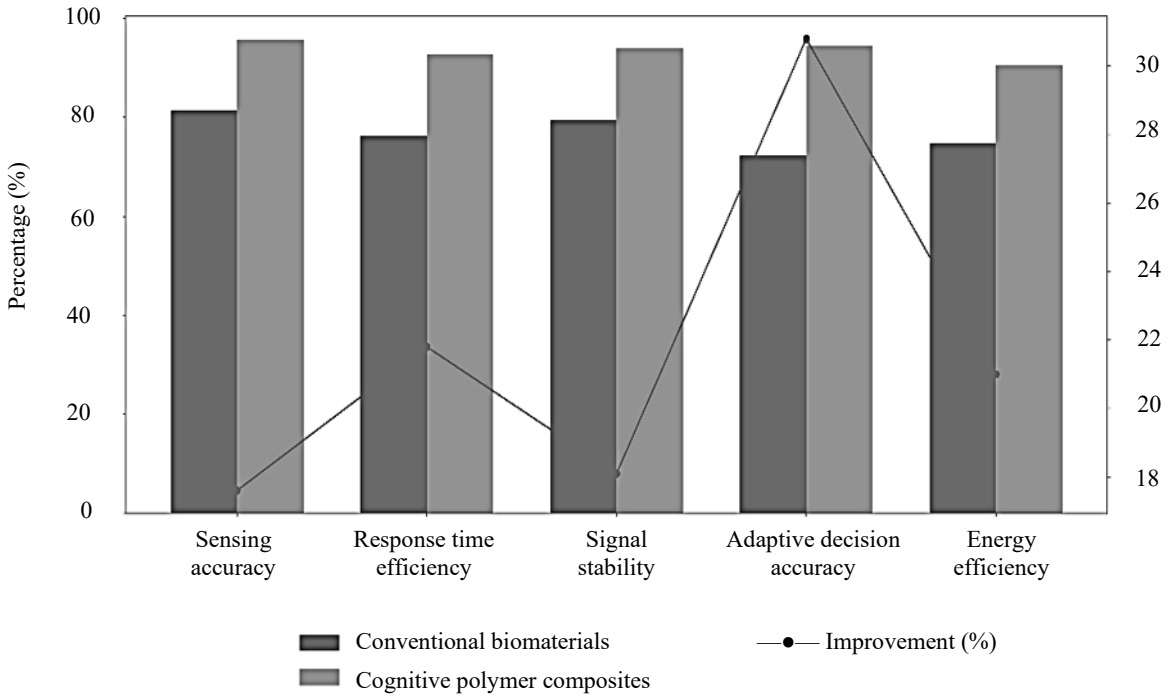


Figure 2. Cognitive polymer composite performance analysis.

A comparison of performance increase in different biomedical measures is given in Figure 2. It also improves the signal stability by 18.1% that becomes 93.9 percent up to 79.5 percent and this ensures the uniformity in the performance because of dynamic conditions. The adaptive decision accuracy is maximized in the results with the results becoming 94.6% versus 72.3% (30.8%) which is a good result of better learning capability.

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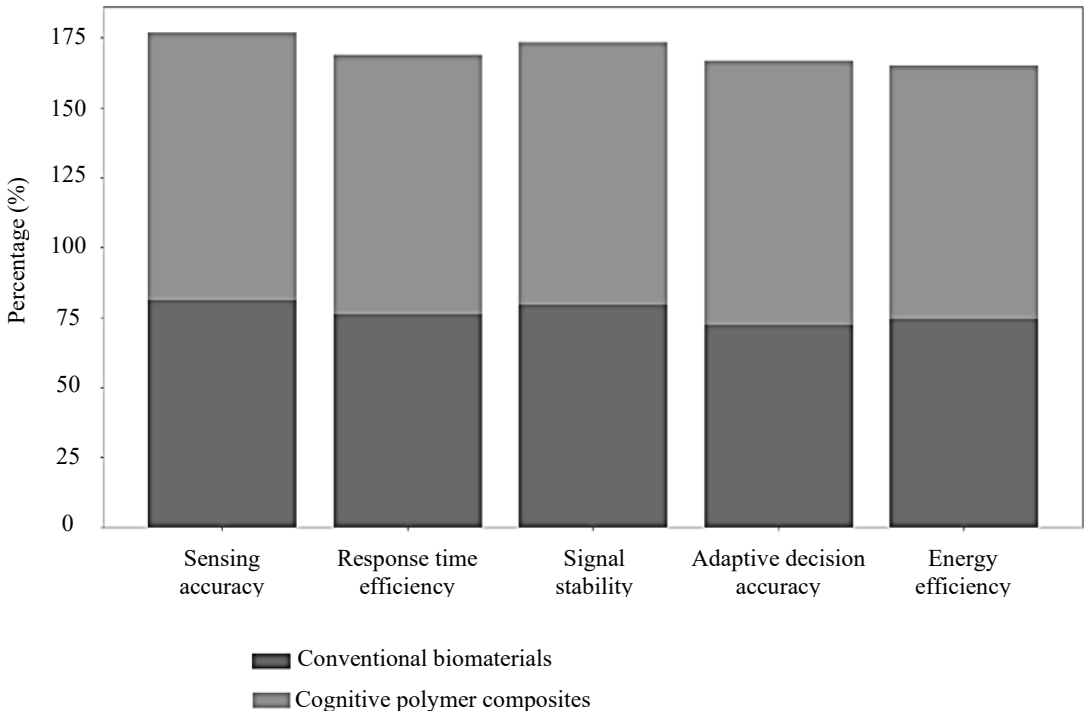


Figure 3. Conventional vs cognitive composite performance distribution.

The analysis of performance distribution between conventional and cognitive composite is represented in Figure 3. In addition, the energy efficiency is also raised to 74.8 per cent to 90.5 per cent that demonstrate efficiency in the utilization of resources and sustainability.

CONCLUSION

In the sense that sensing, computation and adaptive response are built into a single system, cognitive polymer composite systems are a valuable breakthrough in intelligent biomaterials. It has been demonstrated in this paper that the utilization of smart polymers containing embedded sensors and models based on learning can be helpful in offering autonomous biomedical functionality. The proposed system was more precise, sensitive, and faithful as compared to conventional biomaterials. Its capacity to cope with real-time physiological information and dynamically adjust explains good prospects in its application in smart implants, drug-delivery and personalized healthcare. The range of clinical use can be expanded, through future work, by increasing the range of scalability and a long-term biocompatibility, and improved integration with more complex artificial intelligence techniques.

REFERENCES

1. Sikkema R, Baker K, Zhitomirsky I. Electrophoretic deposition of polymers and proteins for biomedical applications. Adv Colloid Interface Sci. 2020 Oct 1;284:102272.
2. Francis A. Biological evaluation of preceramic organosilicon polymers for various healthcare and biomedical engineering applications: A Review. J Biomed Mater Res B Appl Biomater. 2021 May;109(5):744–764.
3. Petropoulos T. A survey of methods and architectures for automatic cervical cancer detection and segmentation using sparsity-aware orthogonal initialization in deep neural network classifiers. ITSI-TEEE. 2025;14(2):32–8.
4. Takawale PS, Amruta G, Sneha J, Rutuja M, Rohan P. A literature review on ProctorSecure AI: Enhancing exam integrity through artificial intelligence and automation. ITSI-TEEE. 2025;13(2):6–11.
5. Aghazadeh MR, Delfanian S, Aghakhani P, Homaeigohar S, Alipour A, Shahsavarani H. Recent advances in development of natural cellulosic non-woven scaffolds for tissue engineering. Polymers (Basel). 2022 Apr 9;14(8):1531.

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6. Pavlidaki T. A survey of methods and architectures for smart healthcare patient monitoring system for IoT-based healthcare system using enhanced residual multi-scale diverged self-attention network. MJRET. 2025;12(2):9–16.
7. Rial R, Liu Z, Messina P, Ruso JM. Role of nanostructured materials in hard tissue engineering. Adv Colloid Interface Sci. 2022 Jun 1;304:102682.
8. Cerdan K, Moya C, Van Puyvelde P, Bruylants G, Brancart J. Magnetic self-healing composites: Synthesis and Applications. Molecules. 2022 Jun 13;27(12):3796.
9. Gupta R, Gupta P, Footer C, Stenning GB, Darr JA, Pancholi K. Tuneable magnetic nanocomposites for remote self-healing. Sci Rep. 2022 Jun 17;12(1):10180.
10. Tao HQ, Yue DW, Li CH. A fast self-healing magnetic nanocomposite for magnetic actuators. Macromol Mater Eng. 2022 Feb;307(2):2100649.
11. Kumar S, Bhowmik S. Potential use of natural fiber-reinforced polymer biocomposites in knee prostheses: A Review on Fair Inclusion in Amputees. Iran Polym J. 2022 Oct;31(10):1297–1319.
12. Ramesh M, Rajeshkumar L, Deepa C, Tamil Selvan M, Kushvaha V, Asrofi M. Impact of silane treatment on characterization of ipomoea staphylina plant fiber reinforced epoxy composites. J Nat Fibers. 2022 Dec 1;19(13):5888–5899.
13. Sontakke AD, Tiwari S, Purkait MK. A comprehensive review on graphene oxide-based nanocarriers: Synthesis, Functionalization and Biomedical Applications. FlatChem. 2023 Mar 1;38:100484.
14. Shi Y, Yang J, Gao F, Zhang Q. Covalent organic frameworks: Recent Progress in Biomedical Applications. ACS Nano. 2023 Feb 14;17(3):1879–1905.

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