

Optimized chaos control in bio-environmental systems

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Abstract

In this study, we are going to examining about microorganisms present in the environment influence the nature of populations affected by psychological disorders. For this objective, we have used two different dynamic systems where the first system is describing the dynamics of the psychologically suffering population, and the second system shows the environmental fluctuations due to the presence of microorganisms. In the Beginning, we coupled these systems through a synchronization procedure with active control. Our aim is to reduce dispersive interactions and find a way to achieve system stability. We are working on the development of a controller based on a genetic algorithm (GA) that provides adaptive tuning of synchronization parameters to improve performance in chaos management. In the final stage, we organizer large-scale numerical simulations for comparative analysis between the GA-based controller and the active control system. This results show that the GA-based controller is capable of achieving faster convergence, higher accuracy in synchronization, and achieving better resistaning response towards system disturbances. Thus, it has proven to be an effective technique for controlling chaos in such complex and dynamical environments.

Subject Classification (2020): 34C28, 34A08, 34A34, 34C15, 45M10.

Keywords: Active control scheme, Chaos synchronization, Genetic algorithm optimization, Microorganism–population interaction, Nonlinear dynamical systems.

1. Introduction

In recent years, crucial progress have been achieved in the area of mathematical modeling of psychological technique in the human body. This progress has been important in the fields of clinical research and biological sciences particularly. Researchers can inspect the fundamental structure of human behavior and its interactions with environmental and social stressors through translating complex psychological and physiological mechanisms into mathematical equations. Not only do these models assist as theoretical frameworks, however they also give clinicians, psychologists, and other medical professionals approach to practical tools that they may use to evaluate the behavior of patients, create therapeutic interventions, and evaluate the outcomes over the long term [1], [2], [3]. Furthermore, in psychology the integration of dynamical systems theory has allowed researchers to examine the nonlinear and often turbulent nature of mental processes. It leads to profound understanding about mental states development under the influence of internal and external components [4], [5].

The main contribution of the principle of *ceteris paribus*, although literally means of 'all other things being equal,' is the construction of simple models of psychological and complex biological systems. This *ceteris paribus* principle has often been used in the fields of medicine and health research to isolate the effect of one variable on utilized of physical or mental health tests, although keeping other variables constant [6], [7], [8], [9]. This method has been effective in the fields of experimental psychology and mental disorders, because it recognizes a controlled assessment of the effects of environmental, pharmacological, or social factors on psychological states [10], [11]. Similarly, this theory is commonly used

in the field of economics for the purpose of analyzing the dynamics of the retail and the decision-making action of humans under the assumption of simplicity [12], [13]. In the scope of psychological modeling, the extension of this method enables researchers to investigate about separate obstacles, such as environmental shocks or social pressure that affect the stability of mental processes while managing for confounding variables [14], [15]. In addition, chaos theory has emerged as an important model for understanding nonlinear systems. The dynamics of chaos has evolved over the years. Researchers have used these models in various scientific fields, such as fluid motion, biological networks, liquid mixing, weather forecasting, and electrical system protection. As psychological and social systems are sensitive to initial conditions, unpredictability, and even long-term irregularities, chaos theory provides an appropriate approach for analyzing these systems [16], [17], [18]. Scientific developments have shown that chaos is related to crowd dynamics, the development of conflicts, and the interaction of populations in social sciences. It has been used in the field of psychology to explain mental fluctuations such as anxiety, depression, or changes in mood, which often follow unpredictable paths when faced with external disturbances [19]. In the study, we shall introduce a dynamic model which draws from the found models, to examine the psychological correlation of three population groups namely (i) mentally distressed individuals, (ii) individuals facing physical stress, and (iii) individuals with a cheerful disposition. This classification shows the basic differentiation of mental states in society. Nonlinear ordinary differential equations (ODEs), representing the temporal evolution of these three populations, are employed to describe the system. It is noteworthy that the establishment exhibits power and authority in public life and allows its business to make profits through investment of other's capital without any fright, therefore competition in the market does not alter the fairness of business [20], [21], [22]. Therefore, it is essential to control chaos in such psychological systems. Active control synchronization strategy refers to a popular notion whereby control inputs are created to minimize the difference between drive and response systems [23], [24]. Active control is attractive due to its simplicity, fast synchronization, and reliance on clear system dynamics. It has proven effective in the domains of engineering, secure communications and biological systems. However, its effectiveness may be limited when faced with noise, uncertainty, or the simultaneous optimization of multiple performance objectives [25]. To overcome these limitations, optimization techniques, especially GA are being very popular. GA explores broad and complex solution spaces using operations such as selection, crossover, and mutation, which are based on Darwin's theory of evolution. Active control needs accurate mathematical modeling for effective response and control. However, even without accurate modeling, GA tend to perform well despite lacking full engineering characteristics. The system components are familiar to us, they are particularly beneficial for securing the accuracy regarding time parameters, reduction in error metrics, and obtaining a balance among on. Contradictory goals like stable robustness and energy control. However, GA

require substantial computational power and are not always suitable for real-time applications. Nevertheless, they perform very well as offline optimization tools to support active control [26], [27]. Comparing GA-based optimization with active control is interesting. GAs are unpredictable, flexible, and global optimizers, whereas active control is clear, efficient, and especially useful when the system parameters are well-defined. Recent research has shown that using GA to optimize the control parameters of active control schemes improves the coordination of chaotic systems. This hybrid technique is stable, adaptive, and efficient, making it ideal for uncertain and nonlinear complex psychological systems [28]. In this study, we developed an active control synchronization method for a psychological model and optimized its parameters using a genetic algorithm. The illustrations show how synchronization can reduce dispersion in sub populations and improve the stability and clarity of the system. By comparing the GA-optimized active control with active control, we demonstrate the advantages and disadvantages of each. Ultimately, this work promotes an interdisciplinary effort to apply evolutionary calculus, chaos control, and dynamical systems theory to the field of psychology. By integrating correction technologies with mathematical precision, it enhances theoretical understanding and finds applications in clinical psychology, psychiatry, and mental health research. By bridging deterministic control methods with stochastic optimization, we provide a novel framework for modeling, analyzing, and stabilizing the complex and chaotic processes of the human mind [29], [30].

2. Mathematical Model Framework

We formulate a novel dynamical model that captures the interactions among three psychologically meaningful subpopulations under the simplifying assumption of the Law of *Ceteris Paribus* as in Figure 1 (i.e., isolating the effect of targeted mechanisms while other influences are held approximately constant).

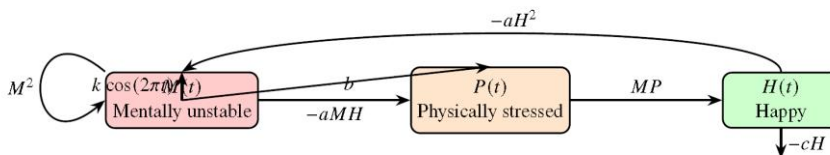


Figure 1
Compartmental diagram of the mental–physical–happy population model with nonlinear feedback, interactions, and external forcing

The population is partitioned into three compartments: $M(t)$: number (or proportion) of individuals experiencing mental stress or anxiety (“mentally unstable”), $P(t)$: number (or proportion) of individuals experiencing physical strain (“physically stressed”) and $H(t)$: number (or proportion) of individuals

who are happy or content (“happy”). The model is based on the following behavioral hypotheses which motivate the interaction terms:

S1: Contact between happy (H) and mentally unstable (M) individuals tends to reduce the happy population (a transfer or conversion from H to M or degradation of H),

S2: The happy class exhibits a natural decline proportional to its current size (background loss/decay)

S3: The physically stressed class grows approximately linearly, representing sustained external pressures or continuous inflow into the physical stress compartment.

Based on these assumptions, we propose the following system of nonlinear ordinary differential equations:

$$\frac{dM}{dt} = M^2 - a H^2 - P + k \cos(2\pi t), \frac{dP}{dt} = -a M H + b, \frac{dH}{dt} = M P - c H, \quad (1)$$

together with initial conditions $M(0) = M_0, P(0) = P_0, H(0) = H_0$, where $M_0, P_0, H_0 \geq 0$ are given and Parameter $a > 0$ controls the strength of this effect of H and $k \cos(2\pi t)$: a time-periodic external forcing acting on M with amplitude k . This represents seasonal, social or environmental periodic stressors (daily/annual cycles). The frequency 2π gives unit period; scale can be adjusted to match real time units. Parameter $b \geq 0$ models continuous sources of physical strain (workload, illness prevalence). $-cH$: is the natural decay of happiness with decay rate $c \geq 0$, as hypothesized in S2.

Connection to control and synchronization

Because the model contains strong nonlinear couplings and an explicit forcing term, it is a suitable candidate for studying chaos control and synchronization. Active control inputs or parameter optimization (e.g., genetic algorithms) can be designed to reduce sensitivity, stabilize equilibria, or synchronize this model with a target trajectory. Subsequent sections will detail controller design, numerical experiments, and optimization strategies for parameter tuning.

In addition to the above, we have modified the model inspired by the framework in [12], where the dynamics of microorganisms is coupled with atmospheric conditions. The focus is on the mutual interactions between bacterial and viral populations within a variable thermal environment. This formulation integrates both biological growth and environmental feedback, making it suitable for investigating ecological and epidemiological complexities even when simplified assumptions are used. Based on this, we have designed a system that involves three time-dependent variables as in Figure 2; $A(t)$: temperature level of the environment (thermal state of the atmosphere), $B(t)$: bacterial population (in particular, “Anthro-Bactor” as a representative microorganism), and $C(t)$: viral population interacting with the bacterial host.

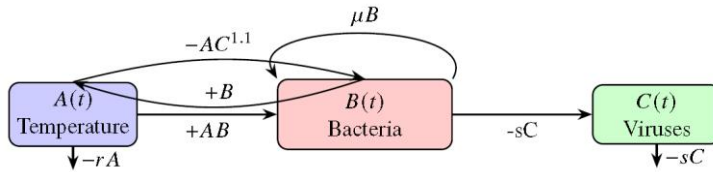


Figure 2
Compact compartmental diagram of the microbial–thermal model showing interactions among temperature (A), bacteria (B), and viruses (C)

The governing equations are motivated by the following assumptions:

P1: The bacterial population grows over time due to favorable conditions, representing sustained microbial reproduction.

P2: The system starts with a relatively high temperature, capturing the influence of climatic or environmental stressors on microbial interactions. Based on these assumptions, the model is described by the nonlinear system of ordinary differential equations:

$$\frac{dA}{dt} = -rA + B, \quad \frac{dB}{dt} = \mu B - AC^{1.1}, \quad \frac{dC}{dt} = AB - sC, \quad (2)$$

with initial conditions; $A(0) = A_0, B(0) = B_0, C(0) = C_0$, where $A_0, B_0, C_0 \geq 0$ represent prescribed starting states and $r > 0$: dissipation rate of temperature, capturing natural thermal loss to the environment, $\mu \geq 0$: intrinsic bacterial growth rate in the absence of viral suppression; and $s \geq 0$: viral decay rate, modeling natural clearance or mortality of viruses.

Connection to control and synchronization

The nonlinearities in (1) render the system sensitive to initial conditions and parameter variations, making it a candidate for chaos analysis and control studies. Just as in psychological or epidemiological models, synchronization strategies (e.g., active control or evolutionary optimization) may be employed to stabilize solutions or align this system with a target trajectory. Such an approach is particularly relevant for ecological management and disease control, where external interventions must counterbalance inherent nonlinear instabilities.

2.1 Dissipativity of the proposed models

Dissipativity (volume contraction) is a fundamental property in nonlinear dynamical systems, as it ensures that trajectories are eventually confined to a bounded absorbing set, guaranteeing the existence of attractors. Therefore, we compute the divergence of the vector field for each of the two proposed models and state interpretable conditions under which dissipativity holds. The divergence of the vector field of the system (1) $F_{\text{psych}} = (\dot{M}, \dot{P}, \dot{H})$ is $\nabla \cdot F_{\text{psych}} = \frac{\partial \dot{M}}{\partial M} + \frac{\partial \dot{P}}{\partial P} + \frac{\partial \dot{H}}{\partial H}$. Computing each partial derivative; $\frac{\partial \dot{M}}{\partial M} = 2M, \frac{\partial \dot{P}}{\partial P} = 0, \frac{\partial \dot{H}}{\partial H} = -c$, so

$$\nabla \cdot F_{\text{psych}} = 2M - c. \quad (3)$$

The system is volume-contracting whenever, $M < \frac{c}{2}$. Thus, dissipativity is achieved provided that the mentally stressed population $M(t)$ remains below the threshold $c/2$. This can be guaranteed if c is sufficiently large relative to the long-term average of $M(t)$. The external periodic forcing $k\cos(2\pi t)$ does not influence the divergence because it depends only on time, not on the state variables. Global dissipativity would require that $M(t)$ is uniformly bounded such that $2M_{\max} - c < 0$. This may be shown using auxiliary Lyapunov bounds or by restricting the parameter set. Negative divergence on average ensures contraction in phase volume, leading to the existence of a bounded attractor—a necessary condition for chaos-control and synchronization studies. The divergence of system (2) as $F_{\text{micro}} = (\dot{A}, \dot{B}, \dot{C})$ is $\nabla \cdot F_{\text{micro}} = \frac{\partial \dot{A}}{\partial A} + \frac{\partial \dot{B}}{\partial B} + \frac{\partial \dot{C}}{\partial C}$. Evaluating the partial derivatives: $\frac{\partial \dot{A}}{\partial A} = -r$, $\frac{\partial \dot{B}}{\partial B} = \mu$, $\frac{\partial \dot{C}}{\partial C} = -s$, so

$$\nabla \cdot F_{\text{micro}} = \mu - (r + s). \quad (4)$$

The system is dissipative provided that, $\mu < r + s$. This means that intrinsic microorganism growth μ must be dominated by combined environmental dissipation terms r and s . The inequality $\mu < r + s$ ensures that natural losses outweigh microorganism growth, preventing unbounded system expansion. If μ is too large relative to $r + s$, divergence becomes positive, leading to potential blow-up unless saturation or nonlinear constraints are imposed. Negative divergence guarantees the existence of an absorbing region, enabling bounded chaotic attractors useful for synchronization analysis.

Numerical illustration for exhibiting the Chaos

For simulations, parameter sets satisfying (3) and (4) should be selected. Numerical integration (e.g. MATLAB ode45) can then be used to demonstrate bounded attractors in phase spaces (M, P, H) and (A, B, C) of the systems (1) and (2). In the *ceteris paribus* system with cosine forcing, the coexistence of nonlinear quadratic growth, bilinear couplings, and periodic external excitation drives the system into a **dissipative yet chaotic regime**. The trajectories remain bounded within a compact absorbing set, ensuring the presence of strange attractors. As illustrated in Figure 3 (a), the phase portrait exhibits a **spiralling attractor structure** that characterizes the persistent nonlinear oscillations generated by the cosine-driven interaction of the variables. This boundedness is necessary to allow for sensitive dependence on initial conditions, while simultaneously preserving physically meaningful dynamics. The *model of microbial interactions* forecasts that a **dissipative yet chaotic regime** will emerge as a result of nonlinear feedback between microbial growth, degradation, and cross-inhibition. Since the dynamics are controlled to a small number of attractors, it is possible to keep away from unbounded divergence while at the same time ensuring the existence of extraordinary attractors. The three dimensional trajectory is revealed in Figure 3 (b), which represents how it eventually preserves on a **spiral attractor** characterized by irregular but

persistent oscillations. These oscillations are a representation of the exquisite competition that exists between microbial proliferation, the constraints of resources, and the nonlinear inhibitory effects. This competition reveals the system's sensitivity to the initial conditions.

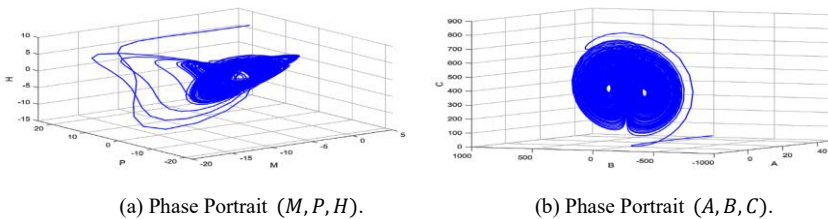


Figure 3

Phase portraits of Ceteris Paribus & Microorganism Interaction Models

The planar of the system (1) embellishes many aspects of this complex interaction, as notice in Figure 4. In the $M-P$ projection, closed loops show up that twist, stipulating that the two variables pass through cycles of suppression and resurgence. In the $M-H$ plane, It is practicable to observe extended spiral bands, that are indicative of the existence of considerable nonlinear feedback between the quadratic growth of M and the damping effect of H . Nevertheless, the $P-H$ projection discloses indistinct yet bounded oscillations that emerges from bilinear couplings and are comforted by the periodic effect of the cosine forcing.

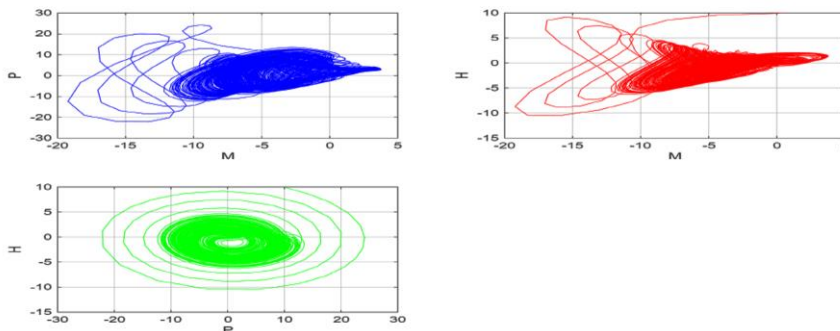


Figure 4

Projection of the Phase Portrait of expression (1)

In Figure 5 (a), the **Lyapunov exponents** of the system (1) verify the chaotic characteristics of the model. One prototype is stable at a positive value, other tends toward zero, and the third endures negative, forming a classical spectrum connected with complete chaos. This configuration estimate the

system's sensitivity to initial conditions and whether strange attractors subsist. The speedy convergence of the spectrum after a quick transient indicates that the numerical method is strong and that forecasting the dynamics over the long term is hard.

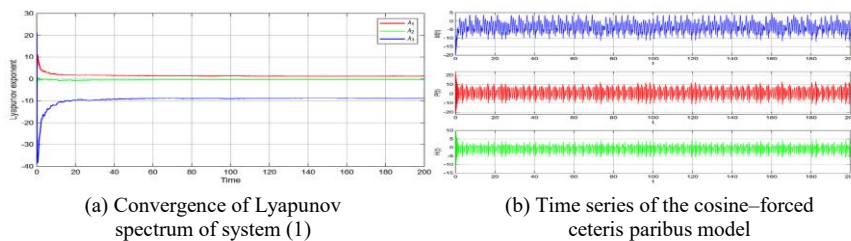


Figure 5

The **time series** Figure 5 (b) shows this chaotic oscillatory behavior even more certainly. The trajectories of $x(t)$, $y(t)$, and $z(t)$ change improperly but remain within certain bounds. This is due to the reality that nonlinear amplification, dissipative damping, and the periodic effects of the cosine component all have thoroughgoing influences on the signal. This stability between order and chaos reveals persistent chaotic oscillations that range with the structure of the attractor and the Lyapunov spectrum. The planar projections of system (2) gives additional insight into the starting dynamics shown in Figure 6. The Projection $A-B$ reveals repeated loops indicating how microbial populations enlarge and contract in response to resource levels. In $A-C$ plane, this is demonstrated by long lasting spiral patterns, which decorate how microbial growth and resource usage interact with one another in a nonlinear manner. At the same time, the $B-C$ projection shows limited and irregular fluctuations created by the nonlinear $AC^{1.1}$ coupling. This adorns how the feedback process of consumption destabilizes the system while generally keeping it boundedness.

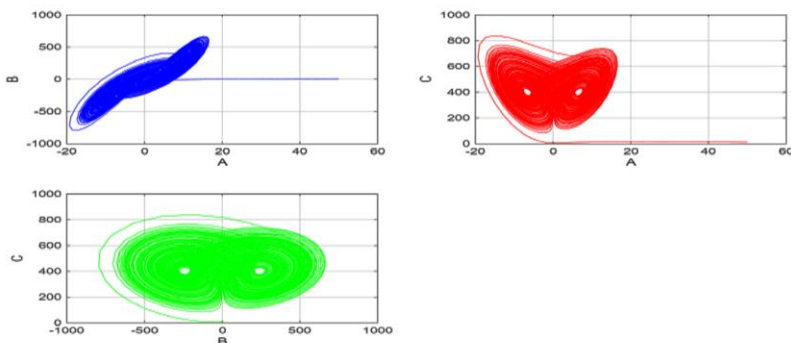


Figure 6

Projection of the phase portrait of system (2)

In Figure 7 (a), the **Lyapunov spectrum** of system (2) provides clear evidence of chaotic behavior. One exponent remains positive, another keeps near zero, and the third approaches a significantly negative value. This design of exponents is a classic sign of deterministic chaos, designating that long-term outcomes will be unpredictable, close by trajectories will diverge rapidly, and oscillations will remain within a bounded range.

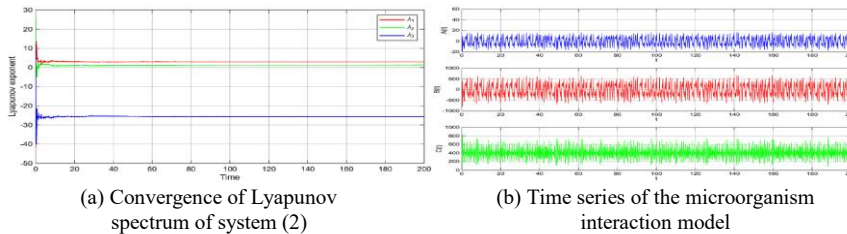


Figure 7

In Figure 7 (b), the **time series analysis** supports these results. The state variables $A(t)$, $B(t)$, and $C(t)$ exhibit fluctuations that are bounded but not regular, which is consistent with the Lyapunov spectrum and the attractor geometry. The fluctuations reflect a dynamic balance between microbial reproduction, decay, and nonlinear consumption, highlighting the system's chaotic persistence and long-term complexity.

3. Chaos Synchronization between the Systems 1 and 2

If System (5) is considered as the **drive system** and System (6) as the **response system**, then the coupled dynamics can be described as follows:

$$\begin{cases} \dot{M}_1 = M_1^2 - aH_1^2 - P_1 + k\cos(2\pi t), \\ \dot{P}_1 = -aM_1H_1 + b, \\ \dot{H}_1 = M_1P_1 - cH_1. \end{cases} \quad (5)$$

$$\begin{cases} \dot{A}_2 = B_2 - rA_2 + V_1(t), \\ \dot{B}_2 = \mu B_2 - A_2C_2^{1.1} + V_2(t), \\ \dot{C}_2 = A_2B_2 - sC_2 + V_3(t). \end{cases} \quad (6)$$

Here, the nonlinear controllers $V_1(t), V_2(t), V_3(t)$ are introduced in the microorganism system (6). To determine the required control functions, we subtract System (5) from System (6). The error state variables are defined as

$$\{E_1 = A_2 - M_1, E_2 = B_2 - P_1, E_3 = C_2 - H_1. \quad (7)$$

The corresponding error dynamics become

$$\begin{cases} \dot{E}_1 = B_2 - rA_2 - (M_1^2 - aH_1^2 - P_1 + k\cos(2\pi t)) + V_1(t), \\ \dot{E}_2 = \mu B_2 - A_2C_2^{1.1} - (-aM_1H_1 + b) + V_2(t), \\ \dot{E}_3 = A_2B_2 - sC_2 - (M_1P_1 - cH_1) + V_3(t). \end{cases} \quad (8)$$

To stabilize the system, the active control functions are chosen as

$$\begin{cases} V_1(t) = W_1(t) - 2B_2 + rA_2 + M_1^2 - aH_1^2 - P_1 + k\cos(2\pi t), \\ V_2(t) = W_2(t) - (\mu - 1)B_2 + P_1 + A_2C_2^{1,1} - aM_1H_1 + b, \\ V_3(t) = W_3(t) - A_2B_2 + (s - 1)C_2 + M_1P_1 - (c - 1)H_1. \end{cases} \quad (9)$$

Theorem 3.1: (Lyapunov design of feedback controllers). *Consider the drive (ceteris paribus) system (5) and the response (microorganism) system (6) with the active terms chosen as in (6). Define the error states; $E_1 = A_2 - M_1$, $E_2 = B_2 - P_1$, $E_3 = C_2 - H_1$, and suppose the controllers W_1, W_2, W_3 are chosen as the state feedback; $W_1(t) = E_2 + P_1 - k_1E_1$, $W_2(t) = -E_2 - 2P_1 - k_2E_2$, $W_3(t) = -k_3E_3$, where $(k_1, k_2, k_3 > 0)$ are constant gains. Then the closed-loop error dynamics are $\dot{E}_1 = -k_1E_1$, $\dot{E}_2 = -k_2E_2$, $\dot{E}_3 = -(1 + k_3)E_3$, and the origin $E = (0, 0, 0)$ is globally exponentially stable. In particular, $E(t) \rightarrow 0$ as $t \rightarrow \infty$ and the two systems synchronize asymptotically.*

4. Numerical Simulation

To verify the effectiveness of the proposed control strategy, numerical experiments were carried out in Matlab. The parameter values for the drive system (1) and the response system (2) were chosen as $r = 36$, $\mu = 20$, $s = 4$, and $a = 5$, $b = 20$, $c = 2$, $k = 20$. The initial conditions for the drive system were set to $M_1(0) = 0.5$, $P_1(0) = 10$, and $H_1(0) = 10$, while the response system was initialized with $A_2(0) = 1$, $B_2(0) = 1$, and $C_2(0) = 9$. Consequently, the initial conditions of the error system (8) are $E_1(0) = 0.5$, $E_2(0) = 9$, and $E_3(0) = 1$.

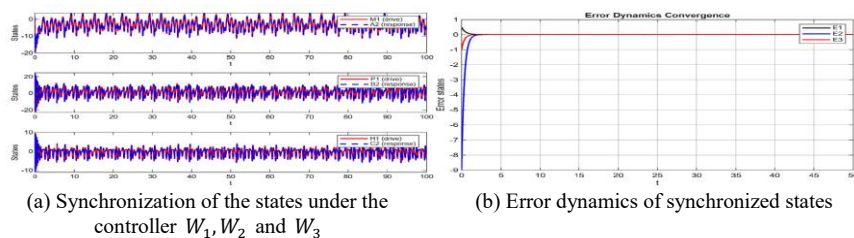


Figure 8

Figures 8 (a) illustrate the synchronization process between the corresponding state variables of the two systems under the control law (9). It can be observed that the trajectories of (M_1, A_2) , (P_1, B_2) , and (H_1, C_2) evolve in unison, confirming successful synchronization. Moreover, Figure 8 (b) presents the behavior of the error dynamics (E_1, E_2, E_3) . As shown, the synchronization errors rapidly decay to zero, demonstrating that the designed controller ensures asymptotic convergence of the response system to the drive system.

5. Genetic Algorithm-Based Controller Optimization

In this study, a genetic algorithm (GA) is employed to optimize the nonlinear control inputs $W_1(t), W_2(t), W_3(t)$ for achieving synchronization between the drive and response systems. To simplify the design while ensuring effectiveness, the controllers are parameterized as state-feedback functions of the error states; $W_1(t) = -k_1 E_1, W_2(t) = -k_2 E_2, W_3(t) = -k_3 E_3$, where $\mathbf{k} = [k_1, k_2, k_3]$ denotes the gain vector to be optimized. These parameterized control functions are then incorporated into the nonlinear control laws of the response system, and the resulting closed-loop dynamics are simulated to evaluate synchronization performance. The optimization objective is formulated as a cost functional that minimizes the integral of the squared synchronization errors, augmented with a regularization term to prevent unbounded growth of the control gains:

$$J(\mathbf{k}) = \int_0^T (E_1^2 + E_2^2 + E_3^2) dt + \alpha \sum_{i=1}^3 k_i^2, \alpha \geq 0. \quad (10)$$

The integral component guaranties precise synchronization for the whole simulation, although the penalty component enhances stability and stops excessive control effort. GA is structured with benefit values (k_1, k_2, k_3) even as decision-making variables and make use of evolutionary operators namely selection, crossover, and mutation to explore the solution space without depending on gradient information. This evolutionary framework assembles it possible to notice optimal control gains that remarkably reduce synchronization error, increase coherence speed, and build the system more powerful to changes in parameters and initial conditions. GA-based controller optimization yields a systematic and flexible framework. GA-based controller optimization is useful for enhancing successful synchronization techniques in chaotic systems.

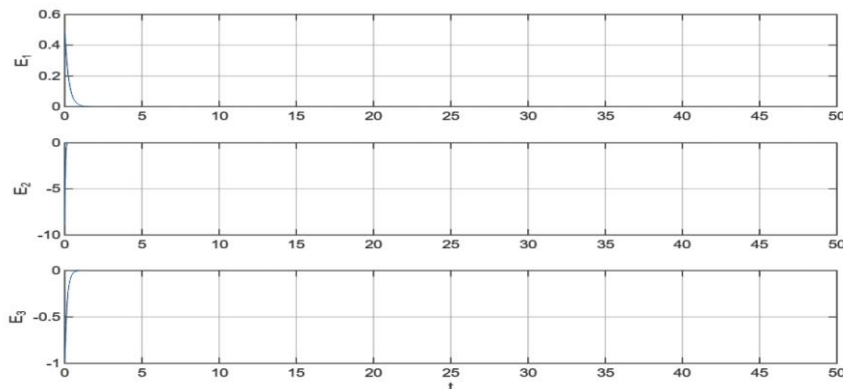


Figure 9
Dynamics of the error with GA-based controller

Error convergence indicates that both the genetic algorithm (GA) and active control methods perform well, even though they operate in completely different

ways. The GA-based method shows a continuous but gradual decrease in error Figure 9, made possible by iterative optimization and adaptive parameter tuning. This evolutionary process allows exploration of the entire solution space, making GA suitable for handling complex nonlinear and uncertain situations. In contrast, the Active Control method achieves faster initial convergence, directly stabilizing the system through deterministic feedback. However, it may be sensitive to parameter variations and lack robustness against strong nonlinearities. In general, GA offers higher adaptability over the long run, whereas Active Control provides immediate stabilization.

6. Conclusion

In this Paper, we have designed the controllers to control the chaotic behaviours of the complex dynamical systems and then synchronize them to analyse the impact of the controllers and observe the existence of chaotic attractors. Firstly, we synchronize the system through an active control process by using a genetic algorithm we have optimized the control gains, for rapid convergence. Further a comparative study is conducted which states that active control provides rapid stabilization, genetic algorithm gives long-term stable states. This framework gives integrated process to regulate the chaos in non-linear biological and ecological systems, which have great application in real world problems.

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Received December, 2025