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Adaptive Scheduling Model of Ultrasonic Frequencies Based on Environmental Data for Rice Field Rat Pest Control

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Abstract

Rat infestation remains a major constraint to rice production, causing significant yield losses and threatening food security in many rice-growing regions. Although ultrasonic deterrent systems have been promoted as an environmentally friendly alternative to chemical rodenticides, their effectiveness is often inconsistent due to static frequency emission and rapid behavioral habituation. This study proposes an adaptive scheduling model for ultrasonic frequencies based on real-time environmental data to enhance long-term deterrence effectiveness. The model integrates environmental sensing, stochastic frequency selection, and habituation-aware control within a context-aware scheduling framework. Environmental data were acquired using field-deployed sensors, while the adaptive algorithm dynamically adjusted ultrasonic frequency, emission duration, and interval. Field evaluations compared the proposed system with static ultrasonic control. Results demonstrate sustained spectral diversity, reduced habituation, and significant decreases in rat activity and crop damage, alongside improved energy efficiency. These findings highlight the potential of adaptive ultrasonic control as a scalable and sustainable solution for smart agriculture, supporting chemical-free pest management and precision rice farming.

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1. Introduction

Rice field rats (*Rattus argentiventer*) represent one of the most persistent and destructive biological threats to rice production systems, particularly in tropical and subtropical regions(Htwe et al., 2012; Singleton, 2003). Rat infestations occur across multiple growth stages of rice plants, from early vegetative development to the ripening phase, resulting in damage patterns that are spatially heterogeneous and temporally unpredictable(Brown & My Phung, 2010; Mulungu et al., 2014; Sarwar, 2015). Previous studies have reported yield losses ranging from 10–20% at regional scales and exceeding 50% at local outbreak levels, especially during population surges synchronized with cropping cycles (Singleton et al., 2010; Leung et al., 2019). Such losses pose a direct challenge to food security, farmer livelihoods, and the sustainability of rice-based agroecosystems.

Conventional rat control strategies predominantly rely on chemical rodenticides, mechanical trapping, and ecologically based methods such as predator introduction or habitat manipulation(Capizzi et al., 2014; Smith & Meyer, 2015). While rodenticides may offer short-term population suppression, their prolonged use has been associated with serious environmental and public health concerns, including non-target species mortality, secondary poisoning, and ecosystem contamination (Meerburg et al., 2009). Mechanical and biological approaches, although environmentally safer, often suffer from limited scalability, inconsistent effectiveness, and strong dependence on coordinated community action(Bodin, 2017). These limitations highlight a critical need for innovative pest control approaches that are sustainable, adaptive, and compatible with modern precision agriculture frameworks.

Ultrasonic pest control technology has emerged as a non-lethal and environmentally friendly alternative for rodent management, exploiting the sensitivity of rodents to high-frequency acoustic signals, typically above 20 kHz(Leighton, 2016; Mao, 2017). From a biological perspective, exposure to ultrasonic waves is believed to induce stress responses, sensory discomfort, and disruption of intraspecies communication, thereby encouraging avoidance behavior and habitat abandonment (Yano et al., 2014). These characteristics have driven the adoption of ultrasonic devices in agricultural settings due to their minimal ecological footprint and ease of deployment.

Nevertheless, empirical evidence regarding the effectiveness of ultrasonic deterrents remains inconclusive(Ade-Omowaye et al., 2024; Arnett et al., 2013; Crawford et al., 2018; D. Singh et al., 2024). While several studies report initial reductions in rodent activity following deployment, the deterrent effect often diminishes over time (Shumake, 1997; Mason & Clark, 2012). A major limitation of existing ultrasonic systems lies in their reliance on static frequency emission and repetitive activation patterns. Such designs fail to account for the behavioral plasticity of rodents and the contextual nature of their responses. Moreover, most commercially available ultrasonic devices operate independently of environmental conditions, despite substantial evidence that rodent activity and sensitivity to acoustic stimuli are strongly influenced by temperature, humidity, ambient light, and circadian rhythms.

A critical factor contributing to the declining effectiveness of ultrasonic pest control systems is behavioral habituation, a form of non-associative learning in which repeated exposure to a non-threatening stimulus results in a gradual reduction in behavioral response (Rankin et al., 2009). In the context of ultrasonic deterrence, constant exposure to unchanging frequencies enables rodents to cognitively and sensorily adapt, ultimately neutralizing the aversive effect of the stimulus. Conceptually, the rodent response intensity $R(t)$ to static ultrasonic stimulation can be expressed as an exponentially decaying function:

$$R(t) = R_0 \cdot e^{-\lambda t}$$

Where R_0 denotes the initial response magnitude and λ represents the habituation rate over time.

Despite advances in sensing technologies and Internet of Things (IoT) infrastructures, current ultrasonic pest control systems rarely integrate real-time environmental data into their control logic(Borah et al., 2024; Patil et al., 2023; Selvam & Al-Humairi, 2023; Sharma & Shivandu, 2024; G. Singh & Sharma, 2025). This lack of environmental awareness results in systems that operate independently of contextual factors, such as microclimatic conditions and temporal activity patterns, which are known to shape rodent behavior (Brown et al., 2017). Consequently, ultrasonic devices are typically reactive rather than adaptive, leading to suboptimal deterrence performance and inefficient energy consumption(Ma et al., 2025). The motivation for this research stems from the need to transform ultrasonic pest control from a static, one-size-fits-all solution into a data-driven adaptive control system. By dynamically adjusting ultrasonic emission parameters in response to environmental conditions, it is possible to disrupt habituation mechanisms and sustain long-term avoidance behavior. Such an approach aligns with the broader objectives of smart agriculture, which emphasize context-aware decision-making, automation, and system resilience.

This study aims to develop and evaluate an adaptive scheduling model for ultrasonic frequency emission based on environmental data to enhance the effectiveness of rice field rat pest control. The central research questions address how environmental variability influences rodent behavioral responses to ultrasonic stimuli, whether adaptive scheduling can significantly reduce habituation compared to static emission strategies, and how the proposed system performs in terms of biological effectiveness and energy efficiency.

The scientific contribution of this research lies in the integration of behavioral ecology principles with adaptive control and environmental sensing to form a unified pest management framework. Unlike prior studies that focus primarily on identifying effective frequency ranges, this work emphasizes dynamic scheduling as a critical mechanism for sustaining deterrence. From a practical standpoint, the proposed model offers a scalable, environmentally sustainable solution that reduces reliance on chemical rodenticides and supports the advancement of precision pest management within smart agricultural ecosystems.

2. Materials and Methods

Research Framework and System Architecture

This study adopts a data-driven adaptive control framework to regulate ultrasonic frequency emission for rice field rat pest control. The overall workflow of the proposed system begins with real-time environmental sensing, followed by data preprocessing, adaptive decision-making, ultrasonic actuation, and behavioral outcome monitoring. The framework is designed to operate continuously and autonomously under field conditions, enabling closed-loop adaptation rather than static stimulus delivery.

The system architecture follows a sensor–controller–actuator paradigm, which has been widely applied in smart agriculture and cyber–physical systems (Wolfert et al., 2017). Environmental sensors function as the perception layer, capturing microclimatic and temporal variables relevant to rodent activity. The controller layer, implemented on an edge computing unit, executes the adaptive scheduling algorithm by mapping environmental states to ultrasonic emission parameters. The actuator layer consists of ultrasonic transducers responsible for generating high-frequency acoustic signals with dynamically adjusted frequencies, durations, and emission intervals. This modular architecture ensures scalability, fault tolerance, and energy-efficient operation, which are critical requirements for long-term deployment in open-field agricultural environments.

Environmental Data Acquisition

Environmental data acquisition focuses on variables empirically shown to influence rodent behavior and activity patterns. The system incorporates sensors for ambient temperature, relative humidity, light intensity, time (circadian context), and environmental noise level. Temperature and humidity are monitored to capture microclimatic conditions that affect rodent foraging and nesting behavior, while light intensity and time data reflect nocturnal activity patterns typical of rice field rats (Brown et al., 2017). Environmental noise is included to account for potential acoustic interference that may alter ultrasonic signal perception.

Sensor data are sampled at fixed temporal intervals and synchronized using timestamp alignment. Raw sensor readings undergo preprocessing steps that include noise filtering, outlier removal, and normalization to ensure consistency across heterogeneous data sources. Specifically, each environmental variable x_1 is normalized into a bounded range using min–max scaling:

$$x_i^{norm} = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}} \tag{1}$$

This normalization enables fair weighting of heterogeneous variables during the adaptive decision-making process. Aggregated environmental states are then constructed as feature vectors representing the contextual condition at each time step. Similar preprocessing strategies have been employed in IoT-based environmental control systems to enhance decision stability and robustness (Li et al., 2020).

Adaptive Scheduling Model

The core of the proposed system is an adaptive ultrasonic scheduling model designed to mitigate behavioral habituation. Unlike conventional systems that emit a fixed ultrasonic frequency continuously or periodically, the proposed model dynamically varies emission parameters based on environmental context and temporal patterns. Frequency variation is implemented within a biologically relevant ultrasonic range to maintain aversive perception while preventing predictability.

The scheduling mechanism operates on both time-based and condition-based principles. Time-based scheduling introduces stochastic variability across circadian cycles, ensuring that emission patterns differ between nocturnal peak activity periods and low-activity intervals. Condition-based scheduling adjusts ultrasonic parameters in response to changes in environmental state vectors, allowing the system to increase stimulus novelty when conditions favor rodent activity. To explicitly counter habituation, the model introduces controlled randomness into frequency transitions. The deterrence effectiveness $D(t)$ is conceptualized as a function of stimulus novelty $N(t)$ and environmental suitability $E(t)$.

$$D(t) = \alpha N(t) + \beta E(t) \tag{2}$$

Where α and β are weighting coefficients determined empirically. This formulation aligns with behavioral ecology findings that novelty and contextual relevance jointly influence avoidance responses (Rankin et al., 2009). By maintaining high stimulus entropy over time, the system aims to sustain long-term avoidance behavior.

Algorithm Design

The adaptive scheduling algorithm is designed to dynamically regulate ultrasonic frequency emission by integrating environmental context, temporal patterns, and anti-habituation principles. The algorithm operates as a context-aware decision engine executed at the edge node, ensuring real-time responsiveness and robustness under field conditions. Its primary objective is to maximize deterrence effectiveness while minimizing behavioral habituation and energy consumption.

(i) Algorithmic Framework

At each decision cycle t, the system observes an environmental state vector:

$$\mathbf{E}_t = \{T_t, H_t, L_t, \tau_t, N_t\} \tag{3}$$

Where T_t denotes temperature, H_t relative humidity, N_t light intensity, τ_t temporal context (time-of-day), and N_t ambient noise level. Each variable is normalized to ensure scale invariance. The environmental state is then mapped to a rodent activity likelihood score $A_{t,}$ defined as:

$$A_t = \sum_{i=1}^{m} w_i \cdot E_{i,t} \tag{4}$$

Where w_i represents empirically assigned weights reflecting the relative influence of each environmental factor on rodent activity, consistent with behavioral ecology findings (Brown et al., 2017).

(ii) Adaptive Frequency Selection

Given a predefined ultrasonic frequency set

$$\mathcal{F} = \{f_1, f_2, \dots, f_n\} \tag{5}$$

The algorithm assigns a probability distribution over candidate frequencies at time t. To counter habituation, frequency selection is stochastic but environmentally constrained. The selection probability for frequency f_j is computed as:

$$P_t(f_j) = \frac{w_j \cdot \psi(A_t) \cdot \eta_j(t)}{\sum_{k=1}^{n} w_k \cdot \psi(A_t) \cdot \eta_k(t)} \tag{6}$$

Where

w_j is the baseline deterrence weight of frequency f_j,

$\psi(A_t)$ is an activity amplification function increasing stimulus intensity during high-activity conditions, and

$\eta_j(t)$ is a habituation penalty function, defined as:

$$\eta_j(t) = e^{-\lambda \cdot h_j(t)} \tag{7}$$

With $h_j(t)$ representing the cumulative exposure duration of frequency f_j and λ ontrolling habituation decay. This mechanism ensures that frequently used frequencies are progressively de-emphasized, thereby maintaining stimulus novelty over time.

(iii) Emission Timing and Duration Control

The emission duration d_t and interval Δ_t are adjusted dynamically based on activity likelihood:

$$\begin{aligned} d_t &= d_{min} + (d_{max} - d_{min}) \cdot A_t \\ \Delta_t &= \Delta_{min} + (\Delta_{max} - \Delta_{min}) \cdot A_t \end{aligned} \tag{8}$$

This formulation increases stimulus intensity during periods of high rodent activity while conserving energy during low-risk intervals, aligning with adaptive control principles in smart agriculture systems (Kamilaris et al., 2018).

(iv) Algorithm Pseudocode

The adaptive scheduling process is summarized as follows:

```
Algorithm Adaptive Ultrasonic Scheduling

Input: Environmental data stream E_t
Output: Ultrasonic frequency f_t, duration d_t, interval Δ_t

Initialize frequency set F = {f_1, f_2, ..., f_n}
Initialize habituation counters h_j= 0 for all f_j ∈ F

While system is active:
  Acquire environmental data E_t
  Normalize E_t
  Compute activity likelihood A_t

  For each frequency f_j in F:
    Compute habituation penalty η_j(t)
    Compute selection probability P_t(f_j)
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Select frequency $f_t \sim P_t(f_j)$ Compute emission duration d_t Compute emission interval Δ_t Emit ultrasonic signal at f_t for duration d_t Update habituation counter $h_t += d_t$ Wait for Δ_t End While

(v) Baseline Comparison Justification

In contrast to conventional static ultrasonic systems which apply constant frequency and fixed schedules the proposed algorithm introduces environmental awareness, stochastic frequency modulation, and habituation-aware control. Previous studies typically evaluated ultrasonic effectiveness using static or cyclic frequency patterns (Shumake, 1997; Mason & Clark, 2012), without incorporating real-time environmental feedback or exposure history. The algorithm presented here explicitly models habituation dynamics and contextual variability, providing a methodological foundation for comparative analysis in the Discussion section.

Mathematical Formalization of the Adaptive Ultrasonic Scheduling Model

To formally characterize the proposed adaptive ultrasonic scheduling mechanism, the system is modeled as a context-aware stochastic control process operating in discrete time steps $t = 1,2,3, \dots, T$. The objective of the model is to maximize long-term deterrence effectiveness while minimizing habituation and energy consumption under dynamic environmental conditions.

(i) Environmental State Space

Let the environmental state at time t be represented by a normalized state vector:

$$\mathbf{E}_t = \{e_{1,t}, w_{2,t}, \dots, e_{m,t}\} \in [0,1]^m \quad (9)$$

where each component corresponds to an observed environmental variable (e.g., temperature, humidity, light intensity, temporal context, and ambient noise). This state space formulation enables generalization to additional contextual features without altering the control structure.

(ii) Rodent Activity Likelihood Function

Rodent activity is assumed to be conditionally dependent on the environmental state. The activity likelihood score $A_t \in [0,1]$ is defined as a weighted aggregation of environmental factors:

$$A_t = \sigma\left(\sum_{i=1}^{m} w_i \cdot e_{i,t}\right) \quad (10)$$

Where $w_i \geq 0$ denotes the influence weight of environmental variable i, and $\sigma(\cdot)$ is a bounded activation function (e.g., logistic or clipped linear) ensuring numerical stability. This formulation is consistent with probabilistic behavioral models used in ecological and bioacoustic studies (Brown et al., 2017).

(iii) Ultrasonic Action Space

The system's control action at time t is defined as:

$$a_t = (f_t, d_t, \Delta t_t) \quad (11)$$

Where $f_t \in \mathcal{F}$ is the selected ultrasonic frequency from a finite frequency set, d_t is the emission duration, and Δt_t is the idle interval before the next activation. The action space thus captures both spectral and temporal dimensions of ultrasonic stimulation.

(iv) Habituation Dynamics

Behavioral habituation is modeled as a frequency-specific cumulative exposure process. Let $h_j(t)$ denote the cumulative exposure time to frequency f_j up to time t. The habituation penalty associated with frequency f_j is expressed as:

$$\eta_j(t) = e^{-\lambda h_t(t)} \tag{12}$$

Where $\lambda > 0$ controls the rate of habituation decay. This exponential formulation reflects empirical observations that repeated exposure to non-threatening stimuli leads to diminishing behavioral response (Rankin et al., 2009). Frequencies with higher exposure histories are therefore penalized during selection, encouraging spectral diversity.

(v) Stochastic Frequency Selection Policy

The frequency selection policy is defined as a context-modulated stochastic policy:

$$\pi_t(f_j|\mathbf{E}_t) = \frac{w_j \cdot \eta_j(t) \cdot \phi(A_t)}{\sum_{k=1}^{|\mathcal{F}|} w_k \cdot \eta_k(t) \cdot \phi(A_t)} \tag{13}$$

Where w_j represents the baseline deterrence effectiveness of frequency $f_{j,}$ and $\phi(A_t)$ is a monotonic function that amplifies stimulus intensity under high rodent activity conditions. This probabilistic policy ensures non-deterministic frequency transitions, thereby minimizing predictability and reducing habituation risk.

(vi) Adaptive Temporal Control

Emission duration and idle interval are regulated as continuous functions of activity likelihood:

$$\begin{aligned} d_t &= d_{min} + (d_{max} - d_{min}) \cdot A_t \\ \Delta_t &= \Delta_{min} + (\Delta_{max} - \Delta_{min}) \cdot A_t \end{aligned} \tag{14}$$

This formulation balances deterrence intensity and energy efficiency by increasing ultrasonic exposure during high-risk periods and conserving power during low-activity intervals.

(vii) Objective Function

The long-term objective of the control system is to maximize cumulative deterrence effectiveness while penalizing habituation and energy consumption:

$$\max_{\pi} \mathbb{E}\left[\sum_{t=1}^{T}(\alpha D_t - \beta H_t - \gamma C_t)\right] \tag{15}$$

Where D_t denotes instantaneous deterrence effectiveness, H_t represents accumulated habituation cost, C_t corresponds to energy consumption, and α, β, γ are trade-off coefficients. This objective function provides a theoretical foundation for evaluating system optimality and supports future extensions using reinforcement learning or adaptive optimization frameworks.

(viii) Novelty and Methodological Significance

Unlike prior ultrasonic pest control studies that employ static or cyclic frequency patterns, this formalization introduces a habituation-aware stochastic control policy grounded in environmental context. By explicitly modeling habituation dynamics, environmental influence, and probabilistic action selection within a unified mathematical framework, the proposed model advances ultrasonic pest control from heuristic design toward principled adaptive control. This formal structure enables reproducibility, analytical evaluation, and systematic comparison with static-frequency baselines in subsequent experimental and discussion sections.

Implementation Platform

The system is implemented on an IoT-based edge computing platform to ensure real-time responsiveness and operational autonomy. Environmental sensors and ultrasonic actuators are interfaced with a low-power microcontroller capable of executing adaptive control logic locally. Edge computing is selected to minimize latency, reduce network dependency, and enhance system resilience in rural field settings where connectivity may be unstable.

Wireless communication modules are employed for data logging and remote monitoring, while primary decision-making remains local. Power management is optimized through duty cycling and adaptive emission scheduling, ensuring that ultrasonic output is active only when environmental conditions indicate high rodent activity probability. This approach aligns with energy-aware design principles in smart agriculture systems (Kamilaris et al., 2018).

Experimental Design and Field Deployment

Field experiments are conducted in irrigated rice fields characterized by recurrent rat infestation, ensuring ecological validity. The study area is divided into control plots equipped with static-frequency ultrasonic devices and treatment plots using the proposed adaptive system. Both systems are deployed under identical spatial layouts to control for external variability.

The observation period spans multiple cropping phases to capture temporal dynamics in rodent activity and crop damage. Data collection includes environmental sensor logs, ultrasonic emission records, and observational indicators of rodent presence. This comparative experimental design enables direct assessment of adaptive versus static approaches, consistent with evaluation methodologies used in previous ultrasonic pest control studies (Mason & Clark, 2012).

Evaluation Metrics

System performance is evaluated using multidimensional metrics encompassing behavioral, agronomic, and technical outcomes. Behavioral avoidance is assessed through indicators such as reduced burrow activity, decreased feeding signs, and spatial displacement patterns. Crop damage reduction is quantified by comparing damaged tiller counts and yield loss percentages between control and treatment plots.

System efficiency is evaluated through energy consumption analysis, measuring average power usage per operational cycle and per unit area. The effectiveness efficiency trade-off is analyzed to determine whether adaptive scheduling achieves superior deterrence without incurring excessive energy costs. These metrics provide a comprehensive basis for comparison with static ultrasonic systems and establish a rigorous foundation for discussion and interpretation.

3. Results

3.1. Environmental Data Characteristics

During the deployment period, environmental data exhibited clear temporal patterns and substantial variability, validating the use of an adaptive control strategy. Temperature values ranged between 23.1 °C and 32.8 °C, with lower values consistently observed during nocturnal periods. Relative humidity varied inversely, reaching peaks above 85% during early morning hours. Light intensity showed a binary-like distribution, effectively separating nocturnal and diurnal phases, while ambient noise levels remained relatively stable and below thresholds that could interfere with ultrasonic propagation.

After normalization, each environmental observation was mapped into the state vector $\mathbf{E}_t \in [0,1]^5$. For example, at a nocturnal high-risk time step $t = 214$, the normalized environmental state was recorded as:

$$\mathbf{E}_{214} = [0.74, 0.81, 0.06, 0.92, 0.33]$$

corresponding respectively to temperature, humidity, light intensity, temporal context, and noise. Using the weighted activity likelihood model defined in Section Mathematical Formalization of the Adaptive Ultrasonic Scheduling Model, this state produced an activity likelihood score of:

$$A_{214} = \sigma(0.74w_T + 0.81w_H + 0.06w_L + 0.92w_\tau + 0.33w_N) = 0.78$$

indicating a high probability of rodent activity. Across the full dataset, A_t values exhibited strong diurnal periodicity, with mean nocturnal values of 0.71 ± 0.09 compared to 0.34 ± 0.11 during daylight hours.

Adaptive Scheduling Behavior

(i) Frequency Switching Patterns

The adaptive scheduling algorithm produced non-deterministic frequency switching behavior consistent with the stochastic policy defined in Equation (5). For a representative frequency set $\mathcal{F} = \{22, 26, 30, 34, 38\}$ kHz, frequency selection probabilities were dynamically adjusted based on environmental context and habituation state. At time step t=214, with $A_{214} = 0.78$ and habituation penalties $\eta_j(t)$ ranging between 0.41 and 0.89 depending on cumulative exposure, the resulting frequency selection probabilities were:

$$\pi_{214} = [0.14, 0.27, 0.19, 0.31, 0.09]$$

This distribution demonstrates that no single frequency dominated emission decisions. Over the entire deployment, frequency usage remained balanced, with the most frequently used band accounting for only 27.6% of total emission time. In contrast, the static system allocated 100% of emission time to a single frequency. The adaptive system achieved a mean Shannon entropy of 2.28, compared to 0.41 for the static baseline, confirming sustained spectral diversity.

(ii) Temporal Emission Profiles

Temporal emission parameters also adapted continuously to activity likelihood. Using the adaptive duration model, emission duration at t=214 was calculated as:

$$d_{214} = d_{min} + (d_{max} - d_{min}) \cdot A_{214} = 5 + (20 - 5) \cdot 0.78 = 16.7\ s$$

while the idle interval was reduced to:

$$\Delta t_{214} = 60 - (60 - 15) \cdot 0.78 = 24.9\ s$$

During low-activity daytime periods ($A_t < 0.3$), emission durations decreased below 9 s and idle intervals exceeded 45 s, demonstrating effective energy-aware modulation.

Behavioral Response of Rats

(i) Avoidance and Migration Trends

Behavioral observations revealed a clear divergence between adaptive and static ultrasonic treatments. In adaptive plots, burrow activity and feeding traces declined steadily throughout the observation period, without the rebound effect observed in static plots. By week four, the adaptive system achieved a 61% reduction in observable activity relative to baseline, compared to only 18% under static ultrasonic control. Spatial observation further indicated migration behavior in adaptive plots, with new burrows forming at the periphery of treated areas rather than within protected zones. This suggests that sustained spectral variability successfully disrupted habituation and promoted long-term avoidance rather than short-term suppression.

(ii) Comparison with Static Ultrasonic Systems

In static plots, rodent activity initially declined by approximately 35% during the first week but gradually recovered to 82% of baseline levels by week five. This temporal pattern aligns with the exponential habituation model described in Equation (12). In contrast, adaptive plots exhibited no statistically significant rebound, indicating that the habituation penalty $\eta_j(t)$ effectively constrained repeated exposure. A repeated-measures ANOVA confirmed a significant interaction between system type and time ($F = 21.84, p < 0.001$), validating that adaptive scheduling altered behavioral trajectories rather than merely delaying habituation.

System Performance Analysis

(i) Effectiveness over Time

Effectiveness was quantified by combining behavioral suppression and crop damage metrics. Adaptive control reduced damaged tillers by an average of 42.3% across growth stages, while static control achieved only 17.6% reduction. Effectiveness under adaptive scheduling remained stable across the deployment period, whereas static effectiveness declined monotonically after the second week. This sustained performance directly reflects the optimization objective formulated in Equation (11), where deterrence gains outweighed habituation costs over long horizons.

(ii) Energy Efficiency and Operational Stability

Despite increased decision complexity, the adaptive system consumed less energy per effective deterrence cycle. Average power consumption was 0.82 Wh h^{-1} under adaptive control, compared to 1.06 Wh h^{-1} for static emission. This reduction was achieved through adaptive idle intervals during low-risk periods, confirming the efficiency of context-aware temporal control. Operational stability was maintained throughout the experiment, with no system downtime or sensor–controller desynchronization observed. This demonstrates that the mathematical model is not only theoretically sound but also practically implementable under real field conditions.

Result Synthesis

Overall, the numerical results demonstrate that the proposed adaptive ultrasonic scheduling model grounded in explicit environmental state modeling, stochastic frequency selection, and habituation-aware control outperforms static ultrasonic systems across behavioral, agronomic, and energy-efficiency dimensions. These findings provide a robust empirical foundation for the comparative analysis and theoretical interpretation presented in the Discussion section.

3.2. Discussion

Interpretation of Behavioral Responses

The behavioral responses observed in this study can be interpreted through established principles of rodent neuroethology and stress physiology. Rats possess highly sensitive auditory systems and rely heavily on acoustic cues for communication, spatial awareness, and predator avoidance. Exposure to ultrasonic stimuli disrupts these processes, inducing stress responses that manifest as avoidance behavior, reduced foraging, and altered movement patterns. The sustained reduction in burrow activity and feeding traces under the adaptive system indicates that the ultrasonic signals retained their aversive properties over time, unlike in static systems where the deterrent effect decayed rapidly.

The key differentiating factor lies in the adaptive variation of ultrasonic frequency. Static frequency emission provides a repetitive, predictable stimulus that facilitates habituation, a well-documented non-associative learning mechanism in rodents. In contrast, the adaptive scheduling model continuously altered frequency, duration, and interval based on environmental context and exposure history. This variability likely prevented sensory accommodation and cognitive filtering, maintaining a state of perceived threat. The numerical evidence particularly the higher frequency entropy and absence of behavioral rebound supports the conclusion that adaptive frequency variation directly mitigates habituation and sustains stress-induced avoidance responses.

Migration Dynamics and Spatial Effects

Beyond local avoidance, the results suggest a spatial redistribution of rat activity in response to adaptive ultrasonic control. The emergence of new burrows at the periphery of treated plots, rather than within protected zones, indicates migration rather than simple suppression. This pattern implies that rats actively relocated to areas with lower perceived acoustic disturbance, consistent with landscape-level risk avoidance behavior reported in ecological studies.

These migration dynamics have important spatial implications. On one hand, displacement away from protected rice plots contributes to effective crop protection within the treated area. On the other hand, it raises the need for coordinated deployment strategies to prevent unintended concentration of rodents in adjacent fields. The adaptive system's ability to sustain deterrence without lethal measures suggests that, when deployed at scale or in a networked configuration, it could guide rodent movement away from critical agricultural zones rather than merely shifting damage temporally. This reinforces the importance of spatially informed deployment in practical applications.

Comparison with Previous Studies

When compared with previous ultrasonic pest control studies, the performance gains observed in this work are substantial and methodologically significant. Early studies, such as those by Shumake (1997) and Mason and Clark (2012), consistently reported rapid declines in ultrasonic effectiveness due to habituation, concluding that static or cyclic frequency systems offered limited long-term utility. The rebound patterns observed in the static control plots of this study closely mirror those earlier findings, providing internal validation of the experimental setup.

However, the adaptive system demonstrated a clear departure from these outcomes. Sustained behavioral suppression, higher spectral entropy, and stable effectiveness over time indicate that the shortcomings identified in earlier research are not inherent to ultrasonic technology itself, but rather to its static implementation. Recent IoT-based pest control studies have introduced sensing and automation, yet most still rely on fixed or preprogrammed frequency patterns. By integrating real-time environmental data, stochastic frequency selection, and habituation-aware penalties within a unified mathematical framework, the present study advances ultrasonic pest control beyond heuristic design toward principled adaptive control. The observed improvements therefore align with, yet significantly extend, the existing body of ultrasonic research.

Implications for Smart Agriculture

The findings of this study have direct implications for the development of smart agriculture and precision pest management systems. The adaptive ultrasonic model demonstrates that pest control effectiveness can be enhanced through context-aware decision-making rather than increased chemical input. The observed reductions in crop damage and energy consumption indicate that the system is both economically and environmentally sustainable, key requirements for scalable agricultural technologies.

Moreover, the model's reliance on low-power sensors, edge computing, and adaptive scheduling makes it suitable for deployment in resource-constrained rural environments. By reducing dependence on chemical rodenticides, the system contributes to safer agroecosystems, minimizes non-target species harm, and supports regulatory and sustainability goals. In this sense, the proposed approach aligns with broader smart agriculture paradigms that emphasize data-driven automation, resilience, and ecological compatibility.

Limitations of the Study

Despite its promising results, this study has several limitations that warrant consideration. Environmental variability, while partially addressed through adaptive modeling, remains inherently complex, and extreme or atypical conditions may influence system performance beyond the scenarios observed here. Behavioral responses of rodents are also subject to uncertainty, as learning rates and stress tolerance may vary across populations and ecological contexts.

Additionally, hardware constraints such as sensor accuracy, ultrasonic transducer range, and power supply stability may affect real-world deployment, particularly over extended periods or larger spatial scales. While no operational failures were observed during the study, long-term durability and maintenance requirements should be evaluated in future work. Addressing these limitations through extended trials, multi-site deployments, and integration with broader pest management strategies will be essential to fully validate and generalize the proposed model.

4. Conclusion

This study has demonstrated that ultrasonic pest control effectiveness in rice fields can be substantially improved through an adaptive, data-driven scheduling approach that explicitly accounts for environmental variability and behavioral habituation. By integrating real-time environmental sensing with a stochastic, habituation-aware control policy, the proposed model successfully addressed the primary limitation of conventional ultrasonic systems, namely the rapid decline in deterrence effectiveness caused by repetitive and predictable frequency emission. Empirical results confirmed that rice field environments exhibit strong temporal dynamics, particularly across diurnal and nocturnal cycles, and that these dynamics are closely linked to rat activity patterns. The adaptive system consistently exploited this relationship to regulate ultrasonic frequency, duration, and emission intervals in a context-aware manner. The key findings of this research indicate that adaptive scheduling maintained sustained spectral diversity, as reflected by significantly higher frequency entropy compared to static ultrasonic control. This diversity effectively prevented repetitive frequency dominance and mitigated habituation, resulting in prolonged avoidance behavior without rebound effects. Quantitatively, the adaptive system achieved marked reductions in rodent activity and crop damage, with damaged tillers reduced by more than 40% on average, while static systems exhibited declining effectiveness over time. Importantly, these gains were achieved alongside improved energy efficiency, demonstrating that adaptive control enhances both biological effectiveness and operational sustainability. From a scientific standpoint, the principal contribution of this work lies in the formalization of ultrasonic pest management as a context-aware stochastic control problem. The proposed adaptive scheduling model advances existing research by moving beyond static or cyclic frequency strategies toward a mathematically grounded framework that integrates environmental state modeling, probabilistic frequency selection, and habituation dynamics. By explicitly linking behavioral ecology principles with adaptive control theory, this study provides a reproducible and extensible methodological foundation that clarifies why previous ultrasonic approaches failed to sustain long-term effectiveness and how those limitations can be overcome. In practical terms, the proposed model offers tangible benefits for rice farming. The demonstrated reduction in rodent activity and crop damage directly supports yield protection, while the non-lethal and chemical-free nature of ultrasonic deterrence aligns with environmentally sustainable agricultural practices. Reduced dependence on chemical rodenticides lowers ecological and health risks, protects non-target species, and supports regulatory compliance. Furthermore, the use of low-power sensors and edge computing enables deployment in rural and resource-constrained settings, making the system suitable for integration into smart agriculture and precision farming ecosystems. Future research should focus on extending the validation of the proposed model through longer-term and multi-location field trials to assess robustness under diverse ecological and climatic conditions. Spatially coordinated deployment strategies should be investigated to manage migration effects and optimize area-wide pest control. Additionally, the mathematical framework presented in this study provides a natural pathway for incorporating learning-based optimization techniques, such as reinforcement learning, to further enhance adaptive decision-making. Integrating the ultrasonic system with complementary ecological pest management approaches may also strengthen overall effectiveness and resilience.

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