Risk Assessment and Management Decisions

www.ramd.reapress.com

Risk. Assess. Man. Dec. Vol. 1, No. 1 (2024) 12–21.

Paper Type: Original Article

Integrated Decision-Making in Production, Maintenance, Repair, and Quality Planning using an agent-based simulation

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Citation:

Received: 12 February 2023 *Revised: 22 July 2023* *Accepted: 25 September 2023*	Nazabadi, M. R., Najafi, E., & Rasinojehdehi, R. (2024). Integrated decision-making in production, maintenance, repair, and quality planning using an optimization approach based on agent-based modeling. *Risk Assessment and Management Decisions, 1*(1), 12-21.

Abstract

This paper investigates the issue of integrated decision-making in production, maintenance, repair, and product quality planning in a single-machine, single-product production system with a single final product inventory. A production machine wears out from the surface, and due to its operation, it is affected by breakdowns and causes them to break down. Performing partial repairs returns the production machine's wear level to its previous state, while complete repairs return it to its initial condition. Unlike previous research, in this study, the possibility of partial maintenance repairs is limited, and reaching the maximum allowable level necessitates unavoidable complete repairs. Additionally, the quality of the final product depends on the production machine's wear and tear level; thus, as the level of machine wear increases, the likelihood of producing low-quality products also increases. At the end of each day, demand enters the system following a Poisson process, and if the final product is available, the demand is met; otherwise, orders are backlogged up to a particular ceiling, and the remaining backlog is considered lost orders. The production system under investigation was modeled in the first step using an agent-based simulation approach to extract an optimal decision combination. In the second step, by employing a simulation-optimization approach, the connection between the agent-based simulation model of the production system and metaheuristic methods was established to extract an optimal policy. The goal is to find a policy that leads to the integrated optimization of the system and minimizes production costs, maintenance and repair costs, inventory holding costs, backlogged orders, machinery breakdowns, and low-quality product production. Four scenarios were designed to evaluate the proposed method. Finally, a comparison was made between the results obtained from the proposed method and production scenarios up to the time of failure and random decision-making. The results showed that the simulation-optimization approach performs up to 30% better than other policies.

Keywords: Simulation, Agent-based, Optimization, Metaheuristic.

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1 | Introduction

Production planning, maintenance, repair, and quality control have always been among the most significant challenges of a production system, directly impacting its output. Production planning aims to make decisions regarding task allocation and scheduling to achieve specific goals, such as minimizing delays or maximizing production output. In maintenance and repair issues, the goal is to maximize machine uptime while minimizing associated costs.

As each maintenance and repair operation renders the machine unavailable, halting production activities and optimizing maintenance and repair procedures without accounting for production planning constraints inevitably yields a suboptimal solution. On the other hand, production planning is heavily influenced by machine uptime. If machines are not available at the required times, achieving the desired objectives in production planning will be almost impossible. Therefore, optimizing production planning without considering maintenance and repair activities will also lead to a suboptimal overall solution. In fact, when maintenance and repair processes are carried out unnecessarily, the time could have been utilized for production. Conversely, allocating time for maintenance and repair to production increases the risk of machine failure and breakdowns. Therefore, maintenance, repair, and production planning are two conflicting activities [1].

On the other hand, the quality of production products is also ultimately affected by how maintenance and repair activities are performed and the consumption level of production machinery. The higher the consumption level of production machines, the lower the possibility of producing low-quality products.

Therefore, production planning, maintenance and repairs, and quality control influence each other entirely, and optimizing each leads to development. However, despite the importance of the topic, very little research has been done by researchers in the field of integrated optimization of the aforementioned areas [2].

The simulation-optimization approach refers to techniques used to optimize parametric stochastic problems [3]. This approach involves searching for input parameter values of a simulation model in a way that achieves the desired objectives or goals.

This research uses the agent-based modeling optimization approach to extract an integrated optimal decision regarding production planning, maintenance, repair, and quality in a deteriorating multi-machine production system. To evaluate the extracted optimal policy results from production policies until failure (Run-to-Failure) and a random decision-maker agent are utilized. It's worth mentioning that the agent-based simulation model was built using anylogic simulation software, and the optquest package was employed to connect the agent-based simulation model with metaheuristic algorithms.

The article's structure will explore the research background and similar studies in the second section. In the third section, the research methodology, including the production system, its simulation using the agent-based modeling approach, and the simulation-optimization approach, will be discussed. The results of the extracted integrated optimal policy will be compared with alternative approaches in the fourth section. Finally, the fifth section will present a summary, conclusions, and suggestions for future research.

2 | Research Background

In recent years, due to the increasing complexity of production systems and continuous changes in customer demands, researchers have focused on optimizing production planning, maintenance, and product quality. These research endeavors can be classified based on problem definition, production system assumptions, and problem formulation. Subsequently, related articles that have addressed integrated optimization in production systems in recent years are described. Numerous studies have examined the economic effects of production, maintenance, repair factors, and product quality [4], [5]. However, only a few studies have simultaneously evaluated the impact of all three areas [2], [6].

Integrated production planning, maintenance, and repair strategies have been investigated in a single-machine, single-product production system with a Preventive Maintenance (PM) policy by Aghezzaf et al. [7]. Chouikhi et al. [8] explored a single-machine production system's combined maintenance and quality issues. In this study, the production system is deteriorating, and its degradation level significantly affects the final product quality. Khatab et al. [9], [10] examined the integrated optimization problem of production planning, quality, maintenance, and repair in a single-machine, single-product production system. Hadian et al. [11] investigated the maintenance, repair, and quality control problems in a deteriorating single-machine production system. The problem has been mathematically modeled through mathematical programming, and genetic algorithms have been employed to find the integrated optimal policy. In a similar production system, Cheng et al. [12] extracted the combined inventory control and maintenance policies using a simulation-optimization approach. The integrated problem of production planning and quality control in a single-machine production system was examined by Bouslah et al. [13]. This study utilized the simulation-optimization approach to extract a combined policy for production planning, inventory control, maintenance, and repair. Simultaneous optimization of production planning and quality control in a single-machine, single-product production system was conducted using the simulation-optimization approach by Rivera-Gómez et al. [10], [14]. To expand on previous research, Rivera-Gómez et al. modeled a deteriorating single-machine, single-product production system to find the optimal production and quality control policy using the simulation-optimization approach [2], [15].

In this study, PM policy was employed to enhance the availability of the production system. Some studies have examined the application of metaheuristic methods in production scheduling and maintenance and repair problems [16], [17]. In these investigations, the production system is of the deteriorating single-machine type, and genetic algorithms, simulated annealing, and learning-based optimization algorithms were utilized to extract the production planning, inventory control, maintenance, and repair policies. Through the review of previous research, it has become apparent that assuming the use of partial repair processes to improve the degradation levels of machinery indefinitely is feasible. However, in a real production system, the number of partial repairs between major repairs is limited, and once this maximum number is reached, the production machine must undergo significant repairs. In this scenario, after major repairs are performed, the degradation level of the production machine is restored to its initial state (with zero degradation). Considering this assumption, this study aims to address this research gap.

3 | Research Methodology

3.1 | Production System

In this study, the problem under investigation is a production system consisting of one production machine and a warehouse with a capacity of $\mathrm{I}_{\max}$. This production system produces only one type of product. The produced products are stored in the warehouse to meet the input demand. The production times follow an exponential distribution with parameter λ_p, and the production cost is determined by C_p. During the production process, the degradation level of the machine changes from state d_0 (like new) to state d_n (failure). The level of machine degradation is defined by d stages, such that after each breakdown leading to wear, the degradation level of the production machine is incremented to $d+1$. This process continues until the degradation level of the production machine reaches the maximum failure level d_{max}. At each stage of degradation $1, \cdots, d_{max}-1$, the production machine can undergo partial repair at a cost of C_m or full repair at a cost of C_r. If a partial repair process is performed, the degradation level of the production machine changes to the previous degradation stage $d-1$. If a full repair process is performed, the degradation level of the production machine changes to d_0. The duration of partial and full repair processes is defined as an exponential distribution with parameters λ_m and λ_r, respectively. Additionally, the maximum number of permissible maintenance activities between two consecutive partial repair activities is limited to U_{max}. At the degradation state d_{max}, the production system becomes faulty and requires full repair activities.

The production process can operate within the degradation levels from d_0 to d_{max-1}. However, when the machine's degradation level reaches d_{max}, full repair activity becomes inevitable, and production halts in this scenario. Additionally, at each degradation level, the production machine may encounter an unexpected breakdown with probability B_d and cost C_b. Maintenance and repair activities can be performed to prevent such unexpected breakdowns. The system's recovery time from breakdown is assumed to follow an exponential distribution with parameter λ_b. It is assumed that $\lambda_b > \lambda_r > \lambda_m$ and $C_b > C_r > C_m$ indicating that the duration and costs increase sequentially from partial to full repairs and unexpected breakdowns.

The production machine's degradation level influences the product's quality. The probability of producing low-quality products is determined by Q_d, which depends on the degradation level of the production machine. Producing low-quality products incurs a cost C_q. As the degradation level of the production system increases, the probability of producing low-quality products also increases. The time between customer demands follows an exponential distribution with parameter λ_d, and the quantity of each demand follows a Poisson distribution with parameter λ_n. Upon arrival of a demand, if the inventory is sufficient, the demand is fulfilled, resulting in a profit P. Otherwise, the demand is backlogged according to the First-Come-First-Served (FCFS) policy. The maximum allowable number of backlogged orders is B_{max}. It is evident that when the system reaches the maximum allowable backlogged orders, subsequent customer demands are considered lost demand, incurring a cost C_l to the system. Inventory holding cost C_h and shortage cost C_s are also considered in this production system.

3.2 | Agent-Based Modeling

Agent-based modeling can be utilized in a system where processes are dynamic, and there is temporal dependency. The agent-based model consists of three main elements:

I. Definition of agents, their attributes, and behaviors.

II. Interactions and communications among agents.

III. Environment.

I. Unlike other common simulation paradigms, such as discrete event simulation and dynamic system modeling, this paradigm takes a bottom-up approach to the problem. It can model and analyze a much wider range of issues with varying levels of detail [18]. This study uses the agent-based approach to construct the simulation model due to the high flexibility of agent-based modeling and the ease of communication between system components. It's worth mentioning that the simulation model has been developed using AnyLogic simulation software. As the main component of the production system in this study, the production agent is responsible for producing the product. This agent has five states.

II. Ready for action: in the initial state, the production agent can receive one of the following messages from the decision-making agent.

III. Production: the production agent, with a degradation level of $0 \leq d < d_{max}$, transitions to the production state with a probability of $1 - B_d$. With a probability of $1 - Q_d$, and after a while of λ_p, it produces a product with acceptable quality. Otherwise, with a probability of B_d, it transitions to the breakdown state and undergoes repair after a time period of λ_b, returning to the initial state. During the production process, with a probability of $f_{d,p}$, the machine's degradation level increases by one unit.

IV. Partial repair: the production agent initiates partial repair activity and, after a time period of λ_m, the degradation level decreases by one unit.

V. Full repair: the production agent initiates full repair activity and, after a time period of λ_r, the degradation level returns to the initial state (d=0), and the state reverts to the initial condition.

VI. Idle: the production agent remains idle until the following demand input.

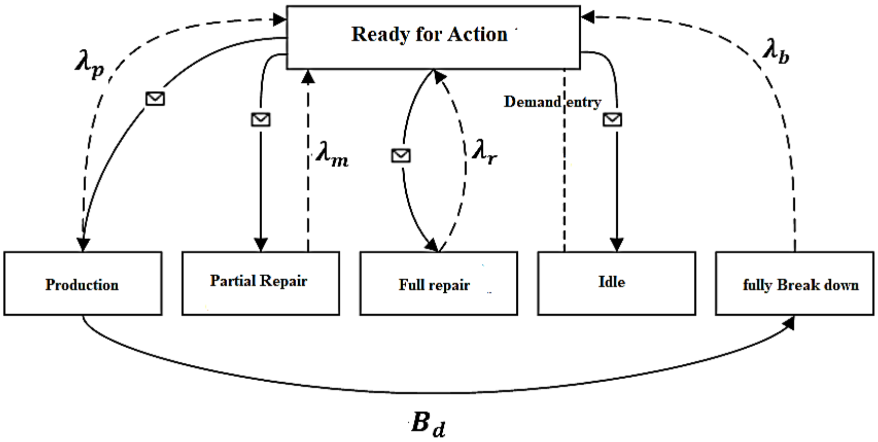

Fig. 1. The behavior of the production agent.

3.3 | Decision Intervals

In order to formulate the decision-making problem and determine suitable points for making integrated decisions, the Semi-Markov Decision Process (SMDP) has been utilized. The reason for using SMDP is the probabilistic nature of transition times for the production agent's state; thus, decision steps cannot be uniform. The effectiveness of decisions on the production agent will be achieved by sending messages to this agent. *Fig. 2* presents the decision intervals for integrated decision-making in the SMDP.

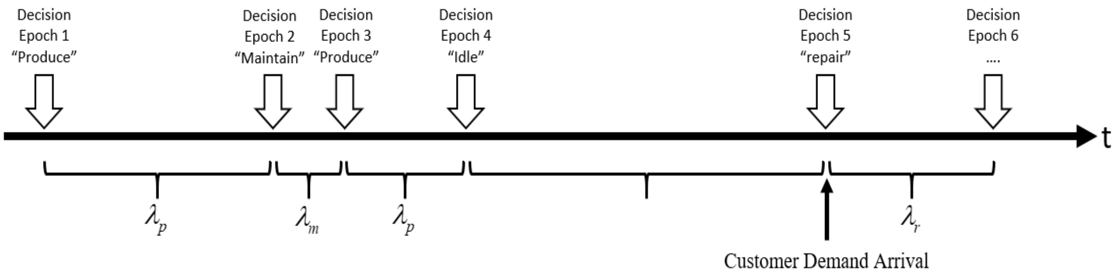

Fig. 2. Semi-markov decision process for integrated decision making.

3.4 | The Integrated Decision-Making Problem Space

The integrated decision-making problem space for production planning, maintenance, repair, and quality control in this research is calculated based on the following equation:

$$N(s) = (d + 1) \times (I_{max} + B_{max} + 1) \times (U_m + 1). \tag{1}$$

The possible actions that can be taken in each state of the system include:

I. Perform production.

II. Perform partial repair.

III. Perform full repair.

IV. Idle the production machine.

It is worth mentioning that an approach combining simulation and optimization will be employed to allocate the best course of action for each state of the problem. This methodology leverages simulation techniques to model the dynamic behavior of the system and optimization algorithms to identify optimal decision strategies. The study aims to enhance decision-making processes and improve performance across various problem states by integrating simulation and optimization.

3.5 | Simulation-Optimization Approach

As mentioned, this research's integrated decision-making problem aims to minimize the objective function, including maintenance costs, product shortages, lost customers, partial repairs, complete repairs, production, and low-quality products, while maximizing the profit from product sales. The objective function is represented by *Eq. 1*.

$$R_{t+1} = C_h(t) + C_b(t) + C_l(t) + C_m(t) + C_r(t) + C_p(t) + C_q(t) - P(t). \quad (2)$$

Where

$$C_h(t) = \left(\int_{t_i}^{t_{i+1}} I(t)dt\right) \times C_h. \quad (3)$$

$$C_b(t) = \left(\int_{t_i}^{t_{i+1}} B(t)dt\right) \times C_b. \quad (4)$$

$$C_l(t) = N(l) \times C_l. \quad (5)$$

$$P(t) = N(P) \times P. \quad (6)$$

After constructing the agent-based simulation model of the production system, its connection with the metaheuristic algorithm is established using the optquest package. This software package utilizes genetic algorithms, simulated annealing, and scatter search to find optimal or near-optimal solutions. Neural networks also adjust the input parameters of the optimization algorithms in this package.

The primary objective of the simulation-optimization approach in this study is to compute optimal values for decision variables (appropriate actions in each problem state) in a manner that minimizes *Eq. 1*. This iterative process continues until no further improvement is observed in the objective function. The relationship between the simulation model and the optimization algorithm is illustrated in *Fig. 3*.

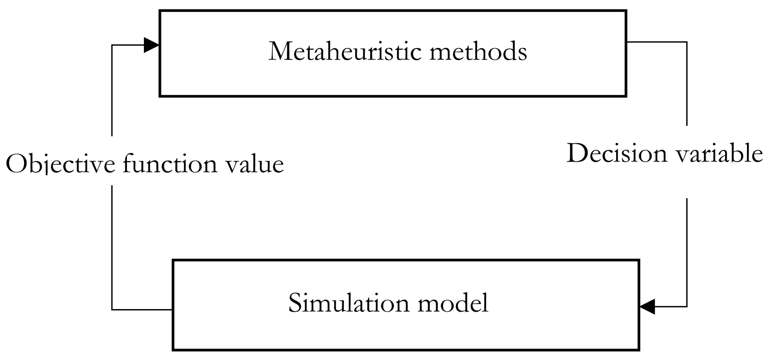

Fig. 3. Iterative simulation-optimization process.

The simulation model is assumed to run for 10,000 hours in each iteration. This duration has been chosen to ensure the occurrence of all possible states of the production system.

4 | Research Findings

Seven scenarios were executed to evaluate the effectiveness of the proposed method, as described in *Table 2*. These scenarios cover various conditions of the system and can be categorized as follows:

I. Base case (scenario 1).

II. Impact of increasing demand rate and its magnitude (scenarios 2 and 3).

III. Impact of a simultaneous increase in demand rate and its magnitude, as well as increasing the probability of breakdowns and producing low-quality products (scenarios 4 and 5).

IV. Impact of simultaneous increase in production rate, demand rate, and its magnitude, as well as increasing the probability of breakdowns and producing low-quality products (scenarios 6 and 7).

The agent-based simulation model of the production system has been initialized using the data provided in *Table 1*.

Table 1. Inputs for the agent-based simulation model.

I_{max}	B_{max}	d_{max}	U_{max}	$f_{d,p}$	C_p	C_m	C_r	C_b	C_q	C_h	C_s	C_l	P
10	10	6	2	(0.04, 0.04, 0.05, 0.05, 0.06, 0.07)	0.5	50	150	300	1.5	0.3	0.6	100	2.1

As shown in *Table 2*, the pressure on the production system gradually increases from the second to the fifth scenario, and relative improvement is achieved in the last two cases. The integrated decision should properly select production, maintenance, and repair activities to prevent lost orders and breakdowns resulting from the increased demands.

Table 2. Various scenarios of the production system.

Q_d	B_d	$1/\lambda_b$	λ_n	$1/\lambda_d$	$1/\lambda_m$	$1/\lambda_r$	$1/\lambda_p$	
(0, 0, 0.01, 0.05, 0.1, 0.15, 1)	(0, 0, 0, 0.001, 0.007, 0.01, 1)	25	2	10	2	20	1	scenario 1
(0, 0, 0.01, 0.05, 0.1, 0.15, 1)	(0, 0, 0, 0.001, 0.007, 0.01, 1)	25	2	6	2	20	1	scenario 2
(0, 0, 0.01, 0.05, 0.1, 0.15, 1)	(0, 0, 0, 0.001, 0.007, 0.01, 1)	25	3	5	2	20	1	scenario 3
(0, 0.02, 0.05, 0.1, 0.15, 0.2, 1)	(0, 0, 0.001, 0.007, 0.015, 0.05, 1)	25	2	6	2	20	1	scenario 4
(0, 0.02, 0.05, 0.1, 0.15, 0.2, 1)	(0, 0, 0.001, 0.007, 0.015, 0.05, 1)	25	3	5	2	20	1	scenario 5
(0, 0.02, 0.05, 0.1, 0.15, 0.2, 1)	(0, 0, 0.001, 0.007, 0.015, 0.05, 1)	25	3	5	2	20	0.5	scenario 6
(0, 0.05, 0.07, 0.1, 0.2, 0.25, 1)	(0, 0.01, 0.02, 0.05, 0.07, 0.1, 1)	25	2	6	2	20	0.5	scenario 7

As mentioned, a comparison was made with the Production Until Failure (RTF) policies and Random Decision Maker (RA) to evaluate the results obtained from the simulation-optimization approach. In the RTF policy, the producer continues production until the equipment reaches its final depreciation state, thus not utilizing partial repairs. The random decision maker selects an action randomly within decision time intervals.

Each scenario in *Table 2* has been implemented in the agent-based simulation model. Then, using the simulation-optimization approach, an optimal integrated decision was extracted. Subsequently, to evaluate it, the value of the objective function obtained (*Eq. 1*) from the simulation-optimization approach was compared with the value of the objective function obtained using the RTF and RA policies. It is worth mentioning that these policies have also been implemented in the agent-based simulation model, and their outputs have been extracted. The evaluation results of the extracted integrated decision are shown in *Fig. 4*.

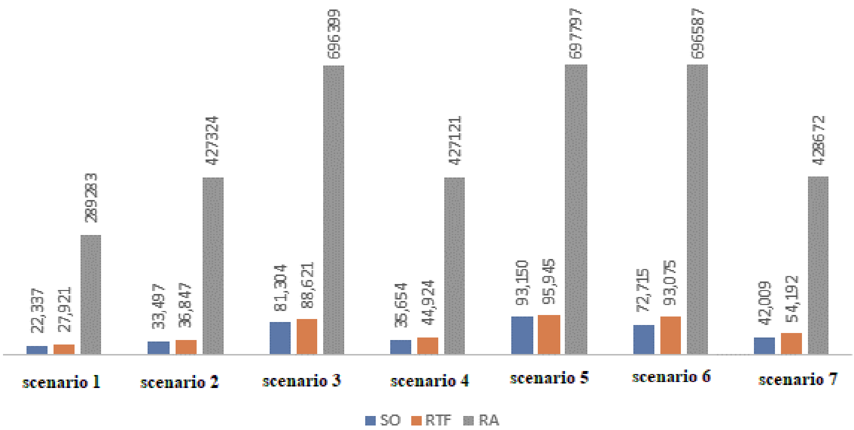

Fig. 4. Results of the optimal integrated decision extracted from the simulation-optimization approach and policies RTF and RA.

As shown in *Fig. 4*, the objective function value obtained from the simulation-optimization approach in all scenarios is lower than that of the other policies. It is worth noting that in scenarios with high pressure on the production system, the gap between the objective function value of the simulation-optimization approach and the production policy until failure is less than when the production system had more freedom of action.

5 | Conclusion

This paper investigated the production, maintenance, repair, and product quality policies in a production system consisting of a deteriorating machine. While extensive research has been conducted on integrated optimal policies, limited attention has been paid to simultaneously examining production, maintenance, repair, and quality issues. Additionally, previous studies have assumed an unlimited repair process for the production system, which does not align with the reality of production systems. This research aimed to extract an integrated decision-making policy considering more realistic assumptions. To this end, agent-based modeling and simulation-optimization approaches have been utilized.

Due to its bottom-up approach, agent-based modeling is highly flexible and suitable for implementing the complexities of production systems. On the other hand, considering the complexities of production systems, it may not be feasible to utilize mathematical problem-solving methods such as Dynamic Programming (DP) due to the problem's dimensions. Therefore, employing metaheuristic algorithms and combining them with agent-based modeling has been suggested.

The Policies from Production to Failure and Random Decision-Making policies have been used to evaluate the integrated optimal decision-making policy for production, maintenance, repair, and quality extracted in this study. Seven scenarios have been designed in the production system to assess the quality of the extracted policy, reflecting various states. These seven scenarios have been formulated by changing the values of production rates, demand rates, machine failure rates, and the probability of producing low-quality products. The defined objective function aims to minimize the maintenance costs of the product, product shortages, lost customers, partial repairs, complete repairs, production, production of low-quality products, and maximize the profits from selling the manufactured products.

The results show that the simulation-optimization approach can improve the objective function by up to 30% compared to other policies. It is worth mentioning that in cases where the production system is under high stress, the improvement may be less than when it has more flexibility. The production-to-failure policy is nearly optimal when the input demand is very high. Therefore, the simulation-optimization approach tends to move towards this policy. However, in cases where the production system is under less stress, the integrated policy extracted from the simulation-optimization method is up to 30% better than the production-to-failure policy.

For future research, it is suggested that machine learning algorithms such as reinforcement learning be utilized to improve integrated decision-making and that the results of the proposed method be compared with those of the proposed method in this study. Additionally, considering production systems with multiple devices and multiple products is recommended.

Author Contribution

Conceptualization and Methodology, M. N. R., Software, Validation, formal analysis, E. N., investigation, R. R.; writing-creating the initial design, M. N. R.; writing-reviewing and editing, E. N. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability

All the data are available in this paper.

Conflicts of Interest

The authors declare no conflict of interest.

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