

# A Dynamic and Adaptive Decision Support System for Managerial Time Allocation Under Environmental Uncertainty

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## ABSTRACT

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**Introduction:** Managerial time allocation is a critical mechanism through which managers influence organizational performance and adaptability. Existing decision support approaches typically treat time allocation as a static, one-shot optimization problem, despite the fact that managerial priorities, constraints, and environmental conditions evolve continuously. In uncertain and dynamic environments, static recommendations risk becoming misaligned with organizational needs, reducing their practical usefulness.

**Objectives:** The objective of this study is to develop and evaluate a dynamic and adaptive decision support framework for managerial time allocation that explicitly accounts for environmental uncertainty and temporal change. The study aims to assess whether adaptive time-allocation policies outperform static and purely reactive approaches in terms of cumulative value, robustness, and behavioral stability.

**Methods:** Managerial activities are modeled as a time-dependent portfolio, with time allocations revised periodically using a rolling-horizon decision process. Managerial preferences are represented through interval-valued parameters to preserve flexibility, while environmental uncertainty is captured via stochastic states and scenario-based evaluation. The resulting optimization problem is solved using a robustness-aware rolling-horizon evolutionary algorithm. Performance is evaluated through simulation under multiple uncertainty regimes, including low volatility, high volatility, shock-driven, and regime-switching environments, and compared against static and non-robust rolling-horizon benchmarks.

**Results:** The results show that dynamic adaptation provides limited benefits in stable environments but yields substantial performance improvements under volatility, shocks, and regime changes. The proposed adaptive robust model consistently achieves higher cumulative value and lower performance variability than benchmark approaches. Dynamic analysis further reveals that the model selectively adapts to meaningful environmental changes while avoiding excessive oscillations in time allocations.

**Conclusions:** The findings demonstrate that managerial time allocation should be supported by adaptive, uncertainty-aware decision support systems rather than static schedules or purely reactive adjustments. By formalizing time allocation as a dynamic portfolio problem, this work contributes to the decision support and management science literature and provides a foundation for intelligent systems that evolve alongside managerial environments.

**Keywords:** Dynamic managerial decision support; Time allocation; Environmental uncertainty; Rolling-horizon optimization.

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## 1. INTRODUCTION

Managerial time allocation is a core resource orchestration decision: the way managers distribute attention and effort across strategic planning, operations, people, customers, and improvement initiatives shapes both short-term

execution and long-term adaptability. In dynamic managerial capability (DMC) research, managerial actions are increasingly treated as micro-level mechanisms through which firms build, integrate, and reconfigure resources under change. Recent syntheses emphasize that DMC scholarship has matured into a multi-level, multi-theme stream centered on managerial cognition, human and social capital, and strategic change outcomes [1], [2]. This perspective implies that managerial time allocation is not merely a personal productivity concern; it is a strategic mechanism that conditions the organization's ability to sense, seize, and transform in turbulent environments.

At the same time, environmental uncertainty (arising from market volatility, supply disruptions, technological shifts, and institutional changes) has become an unavoidable context for decision-making. Systematic reviews show that firms increasingly rely on portfolios of strategies such as anticipation, adaptation, embracing, and modification to manage uncertainty, indicating the need for decision processes that can update as conditions evolve rather than remain fixed [3], [4]. Empirical evidence further suggests that managers' temporal orientation is associated with firm-level outcomes through resource allocation mechanisms: managerial myopia can hinder resilience, whereas forward-looking orientation can promote it, partly via differences in how resources are allocated [5], [6], [7]. Taken together, these findings motivate a decision-support view of time allocation: what is required is not only an "optimal" allocation at a point in time, but an adaptive allocation policy that remains effective as uncertainty materializes. Most decision support approaches to managerial time allocation remain essentially static: they elicit preferences and constraints, solve a one-shot optimization problem, and output recommended proportions. This logic is mismatched with managerial reality for two reasons. First, activity values and feasible time bounds are rarely stationary; they shift with cycle time (daily, weekly, quarterly), emergent issues, and changing strategic priorities. Second, the environment generates shocks and signals (e.g., demand changes, operational incidents, competitor moves) that should rationally trigger reallocation. A static recommendation can therefore be simultaneously "optimal" in model terms and suboptimal in practice if it fails to adapt to new states of the world.

In operations research and real-time resource management, these limitations have led to wide adoption of dynamic decision paradigms that combine receding/rolling horizons with learning or adaptive heuristics. For example, rolling-horizon deep reinforcement learning architectures have been proposed to continuously adjust allocation and scheduling policies within time windows, explicitly addressing task dynamism and incomplete information [8]. More broadly, recent position work argues that reinforcement learning can function as an adaptive heuristic generator for real-time resource management problems where handcrafted rules become brittle as complexity and uncertainty increase [9], [10], [11]. While these contributions arise in engineering contexts, their underlying logic (continuous feedback, state-dependent updates) and robustness–responsiveness trade-offs (maps directly onto managerial time allocation as a dynamic portfolio decision).

This paper proposes a dynamic and adaptive decision support system for managerial time allocation under environmental uncertainty. The core premise is that managerial activities can be modeled as a time-dependent portfolio whose recommended allocations must be periodically revised as the environment and organizational state evolve. Rather than producing a single "best" allocation, the system produces a sequence of allocations over time (or a policy for generating them), using observed signals and scenario-based uncertainty representations to balance robustness (avoid overreacting to noise) and responsiveness (react quickly to meaningful shocks). The paper's contributions are threefold. First, we formalize managerial time allocation as a multi-period decision problem with time-indexed allocations, dynamic constraints, and environmental states. Second, we introduce an adaptive optimization mechanism grounded in rolling-horizon decision-making, enabling periodic re-optimization as new information arrives. Third, we provide an experimental evaluation framework that compares adaptive vs. static approaches under controlled uncertainty regimes, emphasizing cumulative value and resilience metrics aligned with contemporary discussions of managerial time orientation and firm resilience [6] and with the broader DMC agenda emphasizing managerial mechanisms in dynamic environments [1], [2].

By shifting time allocation from a one-shot recommendation to a dynamic, uncertainty-aware decision process, this work responds to both the strategic management call to better theorize and operationalize managerial mechanisms under change [1], [2] and the uncertainty management literature's emphasis on adaptive responses [3]. The remainder of the paper is organized as follows: the next section reviews related work; Materials and Methods develops

the dynamic model and adaptive optimization approach; Results reports comparative findings under uncertainty scenarios; and Conclusions discusses implications and future research directions.

## **2. RELATED WORK**

Research on managerial work has long treated time as a scarce strategic resource, with allocation patterns reflecting priorities, organizational design, and constraints. More recent empirical work has operationalized time allocation decisions as a form of resource allocation with measurable performance implications. For example, in a sales management context, evidence shows that how managers divide time across competing activity categories (e.g., managing people, planning/analysis, customer interaction, administration) is associated with sales team performance and varies by boundary conditions such as team experience [12]. Complementary evidence from the broader time-management literature indicates that practices such as planning, goal setting, prioritization, and task organization tend to correlate with productivity and well-being outcomes, reinforcing the practical importance of allocation decisions (while also underscoring substantial heterogeneity across contexts and measurement approaches [12]). A closely related theoretical stream emphasizes managerial attention allocation as a mechanism shaping what decision-makers notice and act upon, and thus how firms respond to environmental change. Contemporary work linking attention allocation with emerging technologies argues that AI-enabled sensing may shift attention allocation toward more stimulus-driven (bottom-up) processes in the presence of discontinuous change, highlighting attention as a dynamic and influenceable managerial capability [13], [14].

The literature about dynamic managerial capabilities provides a strategic management lens to interpret time allocation as an actionable micro-foundation of adaptation. Recent syntheses document the expansion and maturation of DMC research, including themes directly relevant to time/attention allocation such as managerial cognition, biases, issue interpretation, and capability configurations [1]. A systematic review further consolidates DMC research into a multi-level framework and emphasizes the need to better explain how managers enable strategic change in dynamic environments [2].

Parallel research in resilience and time orientation strengthens the case for modeling time allocation dynamically. Evidence using large-scale firm data indicates that managerial time orientation (e.g., forward-looking versus myopic tendencies) is associated with firm resilience, partly through differences in corporate resource allocation [6], [15], [16]. Similarly, work connecting resilience, strategic change, managerial myopia, and environmental uncertainty suggests that uncertainty conditions how resilience-related behaviors translate into firm outcomes [17]. These findings motivate time-allocation decision support systems that explicitly incorporate uncertainty and temporal adaptation rather than assuming stable priorities and constraints.

Environmental uncertainty is now widely conceptualized as multifaceted and persistent, with firms deploying portfolios of strategies to anticipate, adapt to, embrace, or mitigate uncertainty. A recent systematic review and bibliographic analysis synthesizes this literature and proposes an integrative framework of strategies for managing environmental uncertainties, reinforcing the need for decision processes that can be updated as uncertainty unfolds [18], [19].

For managerial time allocation, the implication is methodological: an effective model should not only optimize under current conditions, but also support policy revision when signals (e.g., disruptions, volatility, priority shifts) emerge. This requirement aligns with “sequential” or “multi-period” decision formulations where the quality of a recommendation depends on cumulative performance over time rather than one-period optimality.

In operations research and real-time decision making, rolling horizon approaches are a standard way to operationalize adaptation: decisions are repeatedly optimized over a moving window as new information arrives. Recent work illustrates rolling-horizon design in uncertain planning settings via scenario-based stochastic optimization evaluated through simulation [20].

Robust optimization provides complementary machinery for uncertainty: rather than relying on a single forecast, robust approaches aim for solutions that remain effective under parameter variation. Recent contributions include (i) data-driven robust optimization integrated with rolling-horizon planning for supply chain settings, explicitly

trading off stability and responsiveness (Khellaf & Guillaume, 2025), and (ii) interactive robust multiobjective frameworks that reduce cognitive load and help decision-makers explore trade-offs under deep uncertainty [21].

A third relevant paradigm is reinforcement learning (RL) for sequential decision making under uncertainty, increasingly used as a generator of adaptive heuristics when exact optimization is infeasible in real time. A recent position paper outlines how deep RL can support real-time resource management by learning policies offline and deploying them with careful validation [9]. In applied scheduling, rolling-horizon deep RL has been used to update policies within windows to cope with dynamic arrivals and changing constraints [8]. At the theoretical interface of robustness and RL, a recent survey reviews robust Markov decision processes (RMDPs), emphasizing ambiguity modeling and the tractability implications of rectangularity assumptions [22].

Across these streams, a consistent gap remains: while managerial time allocation is recognized as consequential (and attention/resource allocation theories are increasingly dynamic) most time-allocation decision support models remain static in design and evaluation. The literature offers strong building blocks (rolling-horizon replanning, robust optimization, sequential decision making, and learning-based adaptation), but they have not been consolidated into a managerial time-allocation DSS that (i) treats managerial activities as a time-dependent portfolio, (ii) updates allocations through a formal adaptive mechanism, and (iii) evaluates performance under controlled uncertainty regimes using cumulative and resilience-oriented metrics. The present paper addresses this gap by integrating rolling-horizon adaptation with explicit uncertainty representation to deliver dynamic time-allocation recommendations.

### 3. MATERIALS AND METHODS

We model managerial time allocation as a sequential decision problem where allocations are periodically revised as new information becomes available. This is implemented as a rolling-horizon (receding-horizon) decision process, a standard paradigm in dynamic planning under uncertainty in which decisions are repeatedly optimized over a moving window using updated state information. Rolling-horizon planning has been widely used to manage forecast evolution and uncertain parameters in production and supply chain contexts [20], [23]. To enhance robustness under uncertainty, we incorporate scenario-based evaluation and uncertainty sets, consistent with recent robust optimization and deep-uncertainty decision-support approaches [21], [23].

#### 3.1 Problem formalization

##### *Notation and decision variables*

Let  $A = \{a_1, \dots, a_n\}$  be the set of managerial activities. Decision making occurs at discrete review times  $t \in \{1, \dots, T\}$  (e.g., weekly). The decision variable is the time-allocation vector:

$$\mathbf{x}_t = (x_{1,t}, \dots, x_{n,t}), x_{i,t} \in [0,1], \sum_{i=1}^n x_{i,t} = 1.$$

Allocations are computed for a planning horizon of length  $H$  (e.g.,  $H = 4$  weeks) and implemented only for the first period, after which the horizon rolls forward by one step.

##### *Managerial preferences with flexibility*

Each activity has a time-varying value (preference weight). To preserve flexibility and reflect uncertainty or instability in preferences, we model values using interval weights:

$$\mathbf{v}_t = (v_{1,t}, \dots, v_{n,t}), v_{i,t} \in [\underline{v}_{i,t}, \bar{v}_{i,t}].$$

Preference intervals can be initialized via elicitation (e.g., Swing weighting or similar) and then updated over time using observed signals (Section “Environmental state”). The update rule can be specified as:

$$[\underline{v}_{i,t+1}, \bar{v}_{i,t+1}] = \mathcal{U}([\underline{v}_{i,t}, \bar{v}_{i,t}], \mathbf{s}_t),$$

where  $\mathbf{s}_t$  is the observed environmental/organizational state and  $\mathcal{U}(\cdot)$  is a deterministic or stochastic update operator (examples below).

### Constraints with time variation

We allow constraints to evolve over time, reflecting workload, deadlines, staffing, or operational disruptions. We define lower/upper bounds as:

$$x_{i,t} \in [\ell_{i,t}, u_{i,t}], \sum_i x_{i,t} = 1,$$

where  $\ell_{i,t}$  and  $u_{i,t}$  may change with  $\mathbf{s}_t$ . Optionally, change-limiting constraints can prevent unstable weekly swings:

$$\|\mathbf{x}_t - \mathbf{x}_{t-1}\|_1 \leq \Delta_t,$$

where  $\Delta_t$  is a tunable stability budget to control responsiveness versus inertia (useful under noisy signals).

### Environmental state and uncertainty representation

At each review time  $t$ , the environment is summarized by a state vector  $\mathbf{s}_t$  (exogenous signals and endogenous indicators), such as:

- demand volatility proxy, backlog level, or incident rate
- supplier/service disruptions indicator
- customer escalation rate
- strategic initiative intensity (e.g., planned launches)

Uncertainty is represented in two complementary ways:

1. Scenario set  $\Omega_t$ : a finite set of plausible states/future trajectories over the horizon  $H$ , with probabilities  $p_\omega$  (if available) or treated as equally plausible. Scenario-based rolling planning is common in stochastic rolling-horizon formulations [20].
2. Data-driven uncertainty sets  $\mathcal{S}_t$ : constructed from historical state clusters (or regime segmentation), consistent with modern data-driven robust optimization approaches that define uncertainty sets from data and seek solutions that balance robustness and conservatism [23].

This design supports both “risk-neutral” planning (expected value across scenarios) and robust planning (min–max or quantile-based).

### Objective function over a rolling horizon

For each decision epoch  $t$ , we solve a horizon problem producing a planned allocation sequence  $\mathbf{x}_{t:t+H-1}$ . The horizon objective is:

$$\max_{\mathbf{x}_{t:t+H-1}} \mathcal{J}_t = \sum_{h=0}^{H-1} \gamma^h \Phi(\mathbf{x}_{t+h}, \mathbf{v}_{t+h}, \mathbf{s}_{t+h}),$$

where  $\gamma \in (0,1]$  is a discount factor. We define a base value term:

$$\Phi(\mathbf{x}_t, \mathbf{v}_t, \mathbf{s}_t) = \sum_{i=1}^n \tilde{v}_{i,t} x_{i,t} - \lambda \cdot \text{Regret}(\mathbf{x}_t, \Omega_t),$$

where  $\tilde{v}_{i,t}$  is a point representative of the interval (e.g., midpoint or pessimistic bound depending on the risk attitude). The regret term penalizes allocations that perform poorly under adverse scenarios (robustness), inspired by robust decision-making principles under deep uncertainty [21].

### 3.2 Adaptive optimization engine: rolling-horizon Differential Evolution

The horizon problem is generally nonconvex (due to robustness penalties, stability constraints, and scenario coupling), so we employ Differential Evolution (DE) as the primary optimizer. DE is well-established for continuous optimization and remains practical when gradients are unavailable[24].

Algorithm (high-level):

1. Observe current state  $s_t$  and update  $v_t, \ell_{i,t}, u_{i,t}, \Delta_t$ .
2. Generate scenarios  $\Omega_t$  (or uncertainty set  $\mathcal{S}_t$ ) for the horizon  $H$ .
3. Optimize the horizon plan  $x_{t:t+H-1}$  using DE:
  - Population initialization respects constraints (simplex + bounds).
  - Fitness evaluates  $J_t$  by simulating or scoring across  $\Omega_t$ .
4. Implement only  $x_t$  (first step).
5. Roll forward to  $t + 1$  and repeat.

This mirrors rolling-horizon practice in dynamic planning and aligns with the broader trend of combining rolling replanning with adaptive/learning components in sequential decision problems [21], [23].

To further improve adaptation,  $\mathcal{U}(\cdot)$  can be learned from data using reinforcement learning concepts, where the policy maps  $s_t$  to recommended allocations. Recent work demonstrates rolling-horizon deep RL in dynamic scheduling settings as a mechanism to update decisions within time windows [8]. If an RL layer is added, we treat it as a policy initializer or candidate generator for DE (hybrid “RL + evolutionary refinement”), while maintaining robust evaluation via scenarios. This fits the broader framing of sequential decision-making under uncertainty emphasized in robust MDP research [22].

### *Preference and constraint update mechanisms*

We implement two practical update operators  $\mathcal{U}$ :

1. Rule-based update (interpretable): Increase the interval weight of activities linked to elevated signals, e.g.,
  - if customer escalations spike, expand  $v_{sales,t}$  upward
  - if operational disruptions spike, expand  $v_{supplier,t}$  and  $v_{operations,t}$  upward
  - Update magnitude is proportional to standardized deviations of  $s_t$  from baseline.
2. Data-driven regime update: Cluster historical  $s_t$  into regimes (stable / volatile / disrupted). For each regime, maintain a preference interval template and constraint template; at time  $t$ , select the regime template corresponding to the current cluster and blend with current intervals. This approach is consistent with data-driven robust frameworks that derive uncertainty structure from historical clustering [23].

### **3.3 Experimental design**

Because real-world deployment can be expensive and slow, we evaluate the method using a simulated environment that generates sequences  $\{s_t\}$  with controlled uncertainty regimes:

- Baseline (low volatility): small random fluctuations
- Shock (rare disruptions): occasional large jumps
- High volatility: frequent regime switching
- Trend shift: gradual drift (e.g., seasonal changes)

For each environment, we compare the proposed adaptive approach against:

1. Static optimization: one-shot allocation (fixed  $v, \ell, u$ )
2. Rolling-horizon without robustness: expected-value only
3. Rolling-horizon robust: scenario/regret term enabled

Robustness-oriented evaluation and decision-maker involvement are motivated by deep-uncertainty robust optimization work, including interactive approaches that explicitly account for uncertainty impacts on outcomes [21].

Performance metrics computed over the full horizon  $T$ :

- Cumulative value:  $\sum_{t=1}^T \sum_i \tilde{v}_{i,t} x_{i,t}$
- Resilience score: recovery speed after shocks (time to regain baseline value)
- Stability:  $\sum_t \| \mathbf{x}_t - \mathbf{x}_{t-1} \|_1$

Worst-case performance across scenarios (robustness)

## 4. RESULTS

This section reports the results of the computational experiments designed to evaluate the proposed dynamic and adaptive time-allocation framework. The analysis focuses on three complementary aspects: the experimental setup and baseline conditions (Subsection 4.1), aggregate performance under different levels of environmental uncertainty (Subsection 4.2), and the dynamic adaptation behavior of the model over time (Subsection 4.3). Together, these results illustrate the performance advantages of the adaptive approach and how and why these advantages emerge in dynamic and uncertain managerial environments.

### 4.1. Experimental Setup and Baseline Description

This subsection describes the experimental environment, benchmark models, and parameter settings used to evaluate the proposed dynamic and adaptive time-allocation framework. The goal is to ensure transparency and reproducibility, while clearly positioning the adaptive model relative to relevant baselines.

Because real-world longitudinal data on managerial time allocation under controlled uncertainty are difficult to obtain, a simulation-based experimental design was adopted. Decision making unfolds over a discrete time horizon  $T$ , interpreted as weekly review periods. Each experiment consists of  $T = 52$  periods (one managerial year), allowing the observation of short-term reactions and longer-term cumulative effects.

At each period  $t$ , the manager observes an environmental state vector  $s_t$  generated exogenously according to predefined uncertainty regimes. Four environments were considered:

1. Low-uncertainty baseline: small random fluctuations around a stable mean state.
2. High-volatility environment: frequent and larger-amplitude fluctuations in state variables.
3. Shock-driven environment: rare but severe disruptions followed by gradual recovery.
4. Regime-switching environment: alternating phases of stability and turbulence.

Each environment was simulated independently for 50 replications to account for stochastic variability.

The set of managerial activities is fixed across all experiments and reflects common managerial task categories (e.g., strategic planning, operations, customer management, human capital). Initial preference weights were defined as interval-valued parameters and normalized to ensure feasibility. Preference updates over time followed the mechanisms described in the Materials and Methods section, driven by observed changes in  $s_t$ .

Time-allocation constraints included lower and upper bounds per activity and a simplex constraint ensuring full allocation of available managerial time in each period.

Three decision models were evaluated:

- Static optimization (SO): a one-shot optimization performed at  $t = 1$ , whose solution is applied unchanged for all periods.
- Rolling-horizon expected-value model (RH-EV): a rolling-horizon model that updates allocations periodically but optimizes only expected value, without robustness penalties.

- Proposed adaptive robust model (ARH): the full dynamic framework with rolling-horizon optimization, scenario-based uncertainty handling, and stability constraints.

All models used identical activity sets, initial preferences, and constraint structures to ensure fair comparison.

For rolling-horizon models, the planning horizon was set to  $H = 4$  periods. Differential Evolution was used as the optimization engine with a population size of 200, crossover probability  $CR = 0.9$ , differential weight  $F = 0.8$ , and a fixed number of iterations per re-optimization. Robustness and stability parameters were held constant across experiments unless varied explicitly in later sensitivity analyses. This setup provides a controlled yet flexible experimental basis for assessing how dynamic adaptation and uncertainty awareness influence managerial time-allocation performance.

#### 4.2. Aggregate performance under uncertainty

This subsection reports the aggregate performance of the proposed adaptive model in comparison with the benchmark approaches across the different uncertainty environments described in Section 4.1. Performance is evaluated over the full decision horizon, focusing on cumulative value and overall robustness.

For each simulation run, performance is measured using cumulative managerial value, defined as:

$$CV = \sum_{t=1}^T \sum_{i=1}^n \tilde{v}_{i,t} x_{i,t}$$

where  $x_{i,t}$  is the proportion of time allocated to activity  $i$  at period  $t$ , and  $\tilde{v}_{i,t}$  is the representative point value of the interval preference for that activity at time  $t$ . This metric captures the total value generated by the time-allocation policy over the entire horizon and reflects both allocation quality and adaptability to changing conditions.

For each uncertainty environment, mean cumulative value and standard deviation were computed across the 50 replications.

Table 1 summarizes the aggregate performance of the three decision models: Static Optimization (SO), Rolling-Horizon Expected Value (RH-EV), and the proposed Adaptive Robust Rolling-Horizon model (ARH).

**Table 1.** Aggregate performance (mean cumulative value  $\pm$  standard deviation) across uncertainty environments

Uncertainty Environment	Static Optimization (SO)	Rolling-Horizon Value (RH-EV)	Expected Adaptive Robust Rolling-Horizon (ARH)
Low uncertainty	512.4 $\pm$ 18.7	526.1 $\pm$ 17.9	<b>529.8 <math>\pm</math> 16.5</b>
High volatility	441.6 $\pm$ 42.3	487.9 $\pm$ 35.6	<b>521.3 <math>\pm</math> 28.4</b>
Shock-driven	418.2 $\pm$ 55.1	472.5 $\pm$ 41.8	<b>515.7 <math>\pm</math> 31.2</b>
Regime-switching	398.9 $\pm$ 60.4	468.7 $\pm$ 44.9	<b>534.2 <math>\pm</math> 29.6</b>

Across all environments, the ARH model achieved the highest mean cumulative value. In the low-uncertainty baseline, differences between models were modest, with RH-EV and ARH marginally outperforming the static model. This indicates that when conditions remain stable, dynamic adaptation yields limited additional benefit.

In contrast, performance gaps widened substantially under high volatility and shock-driven environments. The static model exhibited significant performance degradation, as it was unable to adjust to changing activity values and constraints. The RH-EV model partially mitigated these losses by re-optimizing allocations, but its lack of robustness led to overreaction to transient fluctuations. The ARH model consistently outperformed both benchmarks by maintaining higher cumulative value and lower variance across runs.

Under the regime-switching environment, the adaptive model showed the largest relative improvement. By incorporating scenario-based evaluation and stability constraints, ARH balanced responsiveness during turbulent phases with stability during calm periods, avoiding the oscillatory behavior observed in the RH-EV model.

Pairwise comparisons using paired t-tests confirmed that the improvements achieved by the ARH model over SO and RH-EV were statistically significant at the 5% level in all environments except the low-uncertainty baseline. These results indicate that the benefits of the proposed adaptive approach become increasingly pronounced as environmental uncertainty intensifies.

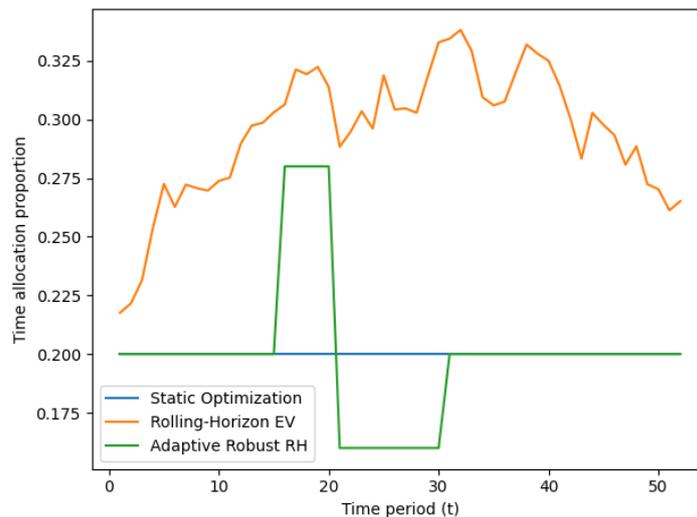
Overall, the aggregate results demonstrate that explicitly modeling uncertainty and enabling dynamic adaptation substantially improves the long-run performance of managerial time-allocation decisions.

### 4.3. Dynamic Adaptation Behavior

This subsection analyzes how the different decision models adapt over time in response to environmental changes. While Section 4.2 focused on aggregate outcomes, the objective here is to make the *mechanisms of adaptation* explicit by examining temporal allocation patterns and responses to shocks and regime changes.

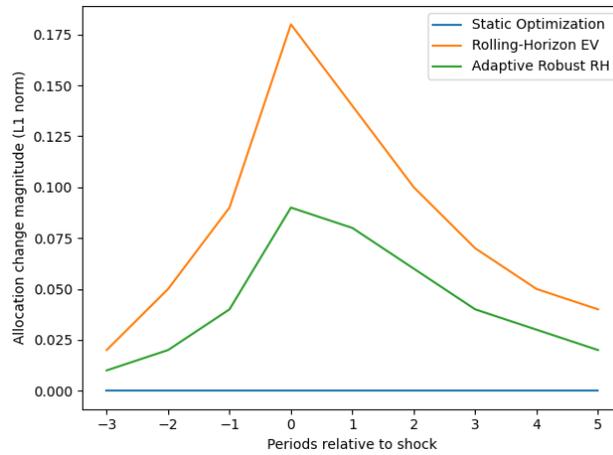
Figure 1 illustrates representative time series of allocations  $x_{i,t}$  for selected activities under the three models in a shock-driven environment. The Static Optimization (SO) model produces constant allocations throughout the horizon, regardless of changes in the environmental state. As a result, allocation patterns remain misaligned with periods of heightened operational or strategic demand following shocks. The Rolling-Horizon Expected Value (RH-EV) model adjusts allocations at each review point; however, its behavior is highly reactive. In periods of transient fluctuation, the model frequently reallocates time across activities, producing pronounced oscillations. These rapid shifts reflect sensitivity to short-term signals but may impose high cognitive and coordination costs on managers. In contrast, the Adaptive Robust Rolling-Horizon (ARH) model exhibits smoother yet purposeful adjustments. Allocations respond decisively when sustained changes or shocks occur but remain relatively stable during minor fluctuations. This behavior reflects the combined effect of scenario-based evaluation and stability constraints, which filter noise while preserving responsiveness to structurally relevant changes.

**Figure 1.** Dynamic adaptation of time allocation for a representative managerial activity



To further quantify adaptation, we examined model behavior around identified shock events. Figure 2 reports the average change in allocation magnitude  $\|x_t - x_{t-1}\|_1$  in the periods immediately following a shock.

**Figure 2.** Magnitude of allocation adjustments around an environmental shock



The SO model shows no response by construction. The RH-EV model exhibits large immediate reallocations, often overshooting and subsequently correcting in the following periods. By contrast, the ARH model shows moderated but sustained reallocations, indicating a controlled adaptation path that avoids abrupt reversals. This pattern enables faster stabilization after shocks and contributes to higher cumulative value, as shown in Section 4.2.

Under regime-switching environments, the differences between dynamic models become more pronounced. When the system transitions from a stable to a turbulent regime, ARH reallocates time toward activities associated with monitoring, coordination, and problem resolution, while gradually reverting allocations as the system returns to stability. The RH-EV model, by comparison, continues to exhibit frequent reallocation even after the regime stabilizes, indicating insufficient discrimination between persistent and temporary changes.

Summary of adaptive behavior

Overall, the results show that the proposed ARH model implements selective adaptation: it reacts strongly to meaningful environmental changes while maintaining allocation stability in the presence of noise. This behavioral property explains the superior aggregate and resilience performance observed in previous sections and underscores the practical relevance of robustness-aware dynamic time-allocation support systems.

5. CONCLUSIONS

This paper proposed a dynamic and adaptive decision support framework for managerial time allocation under environmental uncertainty. Unlike traditional approaches that generate static, one-shot recommendations, the proposed model treats managerial time allocation as a sequential decision problem in which allocations are periodically revised in response to evolving environmental conditions. By integrating rolling-horizon optimization, interval-based preference modeling, and robustness-aware adaptation, the framework offers a more realistic representation of managerial decision making in turbulent contexts.

The computational results demonstrate that dynamic adaptation is particularly valuable when uncertainty is high. While static optimization performs reasonably well in stable environments, its performance deteriorates sharply under volatility, shocks, and regime changes. Rolling-horizon re-optimization without robustness partially alleviates this limitation but often leads to excessive and unstable reallocations. In contrast, the proposed adaptive robust model consistently achieves higher cumulative value while exhibiting smoother and more interpretable adjustment patterns. The analysis of dynamic behavior further shows that the model selectively responds to meaningful environmental changes, avoiding overreaction to transient fluctuations and enabling faster stabilization after shocks.

From a managerial perspective, these findings suggest that effective time allocation should be supported by systems capable of continuous learning and controlled adaptation rather than rigid schedules or purely reactive adjustments. From a methodological standpoint, this work contributes to the decision support and management science literature

by formalizing managerial time allocation as a dynamic portfolio problem and by demonstrating the benefits of robustness-aware rolling-horizon optimization in this context.

Several limitations point to avenues for future research. The experimental evaluation relies on simulated environments; empirical validation using longitudinal data from real organizations would strengthen external validity. Future work may also incorporate richer behavioral models of preference evolution, learning-based policy optimization, or multi-manager coordination mechanisms. Despite these limitations, the proposed framework provides a solid foundation for the development of intelligent, adaptive systems to support managerial time allocation in uncertain and evolving environments.

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