SIMULATION AND OPTIMIZATION OF A PARSEC SYSTEM-OF-SYSTEMS ARCHITECTURE

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Abstract:

This paper presents the final system-of-systems architecture of the PARSEC parcel screening concept and its integrated simulation–optimization framework. Following modifications in the technological configuration, including the introduction of computed tomography and revised decision logic, the analytical and simulation models were updated accordingly. A probabilistic formulation of system-level detection and false alarm rates was developed, explicitly incorporating the P/I shielded branch. A mixed-integer linear programming model was formulated to select optimal ROC operating points under security and capacity constraints and solved in MATLAB. The proposed framework provides a structured methodology for evaluating detection performance and operational feasibility in high-throughput parcel environments.

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1 Introduction

The rapid growth of cross-border e-commerce has resulted in a substantial increase in international parcel volumes, placing significant pressure on customs and security authorities. In the European Union alone, the number of low-value e-commerce shipments reached approximately 4.6 billion items in 2024, corresponding to nearly 12 million parcels per day, reflecting a substantial multi-year increase in parcel flows related to online trade [1]. The increasing volume of small consignments significantly affects customs control processes, operational workloads and resource allocation in postal and express courier systems [1].

Previous research highlights the dynamic interaction between cross-border e-commerce and international logistics systems, emphasizing that growing trade volumes require increasingly efficient and scalable logistics infrastructures [2]. Recent research highlights the increasing role of advanced analytical and artificial intelligence methods in logistics system design and optimization, particularly in complex and high-throughput environments [3]. In high-throughput parcel environments, maintaining high detection rates of illicit goods while preserving flow efficiency becomes a critical design problem. The fundamental trade-off between detection probability and false alarm rate directly influences manual inspection workload, processing times and operational costs.

Several research and innovation initiatives have therefore focused on improving non-intrusive inspection technologies and integrating them into multi-stage screening architectures. One example is the Horizon Europe project PARSEC, which aims to develop and evaluate a multi-stage system-of-systems (SoS) detection architecture for postal and express courier flows. The initial architecture and its corresponding discrete-event simulation (DES) model were presented in an earlier publication [4].

During the course of the project, modifications were introduced in the technological configuration, including the replacement of the originally planned third-stage inspection technology with a computed tomography (CT) system. This change resulted in a revised hierarchical structure and modified decision logic within the system-of-systems. Consequently, both the simulation model and the analytical formulation of system performance required adaptation.

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The objective of this paper is therefore threefold. First, to present the final PARSEC system-of-systems architecture and its corresponding simulation model. Second, to provide a formal analytical formulation of system-level performance indicators. Third, to introduce a mixed-integer linear programming (MILP) optimization model for selecting ROC operating points of individual technologies, integrated with discrete-event simulation for operational validation.

The remainder of the paper is organized as follows. Section 2 describes the final PARSEC system-of-systems architecture. Section 3 presents the simulation model of the revised configuration. Section 4 introduces the analytical formulation of system performance. Section 5 defines the MILP optimization model. Section 6 discusses the integration of optimization and simulation and the implications of the obtained results.

2 PARSEC system-of-systems architecture

The final PARSEC system-of-systems (SoS) architecture has been developed to address the operational trade-off between detection performance and inspection workload in high-volume parcel environments. The architecture integrates multiple non-intrusive inspection technologies into a hierarchical, multi-stage screening structure supported by risk analysis and human inspection. The overall concept of the final configuration is illustrated in Figure 1.

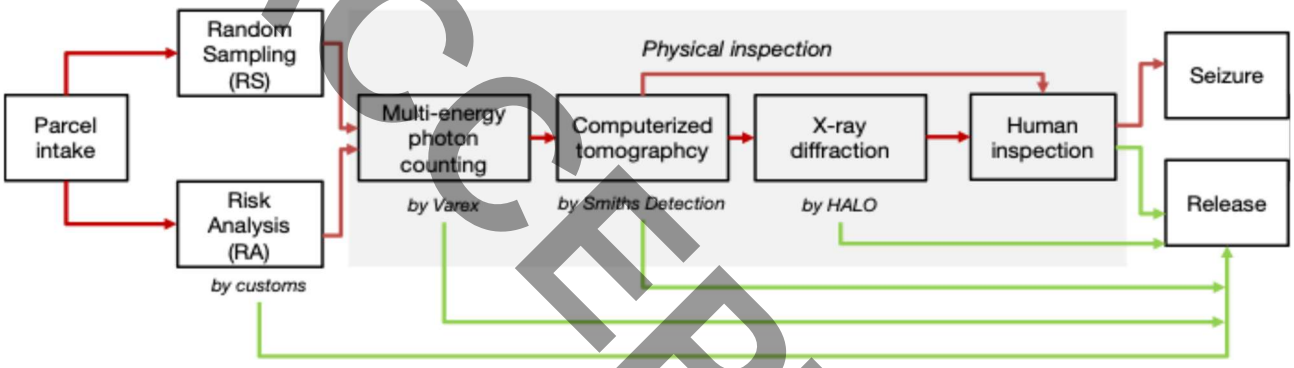


Figure 1. Final PARSEC system-of-systems architecture

The screening process begins with risk analysis (RA), which selects a defined percentage of incoming parcels for further inspection. In addition, a random sample (RS) of parcels is included to monitor the effectiveness of risk profiling and to ensure continuous system calibration.

The first screening stage consists of a high-speed dual-energy photon counting detector operating on the primary conveyor line. This stage is designed to process large parcel volumes with minimal delay while identifying potentially suspicious consignments based on selected ROC operating points.

Parcels flagged at the first stage are diverted to a resolution lane composed of two complementary technologies: computed tomography (CT) and X-ray diffraction (XRD). These technologies operate in a coordinated decision structure. The CT system performs volumetric imaging and threat detection, while the XRD system provides material discrimination capabilities. Depending on the classification outcome and predefined operating thresholds, parcels may be cleared for release or forwarded to human inspection.

Human inspection represents the final verification stage, where parcels identified as suspicious are physically opened and examined. In the modeling framework, this stage is assumed to provide full classification accuracy.

Compared to the initially proposed architecture presented in [4], the final configuration reflects a revised technological hierarchy and modified decision logic resulting from changes in the available inspection technologies. In particular, the integration of computed tomography as a core element of the resolution lane required adaptation of the screening sequence and performance modeling approach.

The presented architecture forms the structural basis for the simulation and optimization models described in the following sections.

3 Simulation model

To evaluate the operational performance of the final system-of-systems configuration, a discrete-event simulation (DES) model was developed. The model represents parcel flows from risk-based selection through

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multi-stage screening and final release or human inspection. The simulation scenario used for analysis is illustrated in Figure 2.

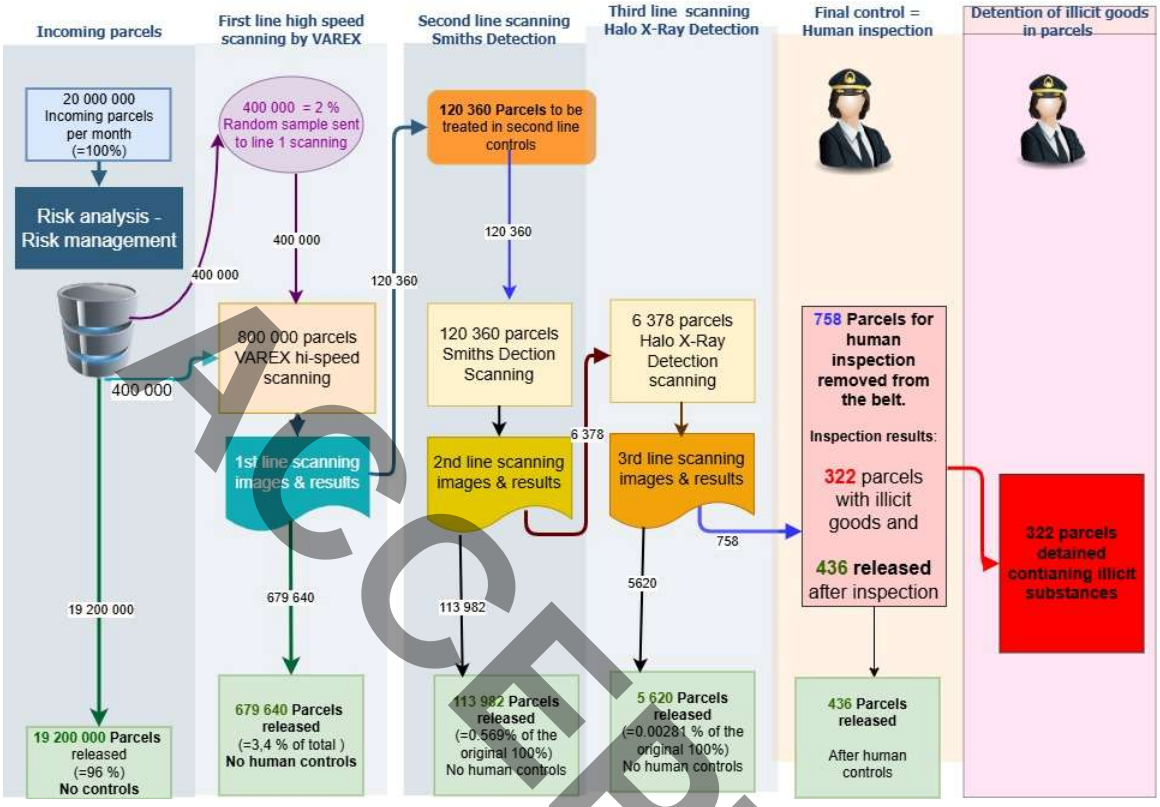


Figure 2. Simulation scenario of the PARSEC system-of-systems

The scenario assumes a high-volume parcel terminal environment in which a predefined share of incoming parcels is directed to the screening system based on risk analysis (RA), complemented by a random sampling (RS) mechanism. Parcels entering the screening system are statistically classified as positive or negative according to a predefined prevalence parameter.

The logical implementation of this scenario within the discrete-event simulation environment is shown in Figure 3.

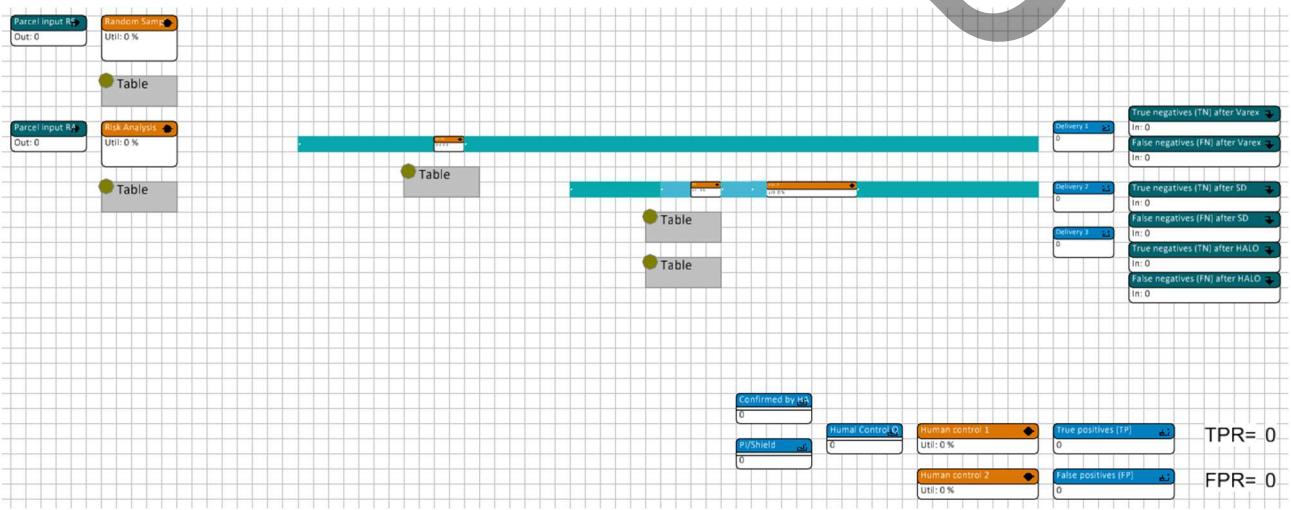


Figure 3. Layout of the discrete-event simulation model

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The DES model's structure follows the architectural logic presented in Section 2, while explicitly modeling processing resources, queues, conveyors and decision nodes corresponding to individual screening stages. The model captures the sequential and conditional routing of parcels between the first screening stage, the resolution lane and the human inspection stage.

The key input parameters of the simulation include:

- total parcel throughput entering the system-of-systems,
- prevalence of illicit goods in the inspected flow,
- ROC operating points of individual inspection technologies,
- processing times of automated screening stages,
- human inspection time and available inspection capacity.

The primary performance indicators evaluated in the simulation are:

- system-level true positive rate (TPR),
- system-level false positive rate (FPR),
- number of parcels forwarded to human inspection,
- utilization of screening technologies and human inspectors,
- queue formation and waiting times.

While analytical expressions can describe static system-level detection performance, the DES model enables evaluation of dynamic operational effects, particularly under high utilization conditions and varying threshold configurations. It therefore provides the operational validation layer required for assessing feasibility and capacity constraints of the final PARSEC architecture.

4 Analytical formulation of the system-of-systems performance

To complement the discrete-event simulation analysis, the performance of the multi-stage system-of-systems is described analytically using probabilistic modeling. The analytical formulation follows the final PARSEC decision logic, including the case of parcels flagged by Smiths Detection (SD) as suspicious but classified as P/I shielded and therefore routed directly to human inspection without HALO scanning.

All symbols are defined at their first occurrence in the text. Let X denote the number of parcels entering the system-of-systems and p the prevalence of illicit goods in the inspected flow. The number of positive parcels is $P = pX$ and the number of negative parcels is $N = (1-p)X$. For each automated stage i, let d_i denote the probability of detection and f_i the probability of false alarm. In the considered configuration, the stages are: Varex (index V), Smiths Detection (index S), and HALO (index H). Furthermore, let p_{PI} denote the proportion of SD-alarmed parcels that are P/I shielded and cannot be scanned by HALO, thus being forwarded directly to human inspection.

Following the flow decomposition, the expected number of true positives (TP) forwarded to human inspection consists of: (i) positives alarmed by Varex and SD and then routed directly to human inspection due to P/I shielding, and (ii) positives alarmed by Varex and SD, scanned by HALO, and alarmed by HALO:

$$TP = d_V \cdot d_S \cdot p_{PI} \cdot P + d_V \cdot d_S \cdot d_H \cdot (1 - p_{PI}) \cdot P \tag{1}$$

The expected number of false negatives (FN), i.e., positive parcels released to delivery, includes positives missed by Varex, missed by SD after being alarmed by Varex, and missed by HALO after being alarmed by Varex and SD and being non-shielded:

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$$FN = (1 - d_V) \cdot P + (1 - d_S) \cdot dV \cdot P + (1 - d_H) \cdot d_S \cdot d_V \cdot P \cdot (1 - p_{PI}) \quad (2)$$

Analogously, the expected number of false positives (FP), i.e., negative parcels forwarded to human inspection, is:

$$FP = f_S \cdot f_V \cdot N \cdot p_{PI} + fH \cdot f_V \cdot f_S \cdot N \cdot (1 - p_{PI}) \quad (3)$$

Finally, the expected number of true negatives (TN), i.e., negative parcels released to delivery, is:

$$TN = (1 - f_V) \cdot N + (1 - fS) \cdot f_V \cdot N + (1 - f_H) \cdot f_S \cdot f_V \cdot N \cdot (1 - p_{PI}) \quad (4)$$

These expressions satisfy conservation identities $TP + FN = P$ and $TN + FP = N$.

The system-level true positive rate and false positive rate are defined as:

$$TPR_{sys} = TP / P \quad (5)$$

$$FPR_{sys} = FP / N \quad (6)$$

Substituting (1) and (3) yields compact forms:

$$TPR_{sys} = d_V \cdot d_S \cdot (p_{PI} + d_H \cdot (1 - P_{PI})) \quad (7)$$

$$FPR_{sys} = f_V \cdot f_S \cdot (p_{PI} + f_H \cdot (1 - p_{PI})) \quad (8)$$

The analytical formulation provides a fast estimate of the static system-level performance for a given set of operating points (ROC thresholds). However, it does not capture dynamic operational effects such as queue formation and capacity saturation; therefore, it is complemented by the discrete-event simulation model described in Section 3 and by the MILP optimization model in Section 5.

5 MILP optimization model

Based on the analytical expressions derived in Section 4, a mixed-integer linear programming (MILP) model is formulated to select optimal ROC operating points of the individual inspection technologies. The model explicitly incorporates the P/I shielded branch through the system-level expressions for TPR_{sys} and FPR_{sys}.

Finite sets of admissible ROC operating points are defined for each technology. Each configuration corresponds to a combination of operating points of Varex, Smiths Detection and HALO. For every configuration, the corresponding system-level detection rate, false alarm rate and expected human inspection workload are precomputed.

The MILP model selects exactly one configuration by means of binary decision variables. Two optimization variants are considered:

- maximization of the system detection rate subject to an upper bound on the false alarm rate,
- minimization of the false alarm rate subject to a required minimum detection rate.

Operational feasibility is ensured through capacity constraints, primarily limiting the expected workload of human inspection and, if necessary, automated screening stages.

The complete mathematical formulation of the optimization model corresponding to Variant A (maximization of TPR_{sys}) is presented below on Figure 4. The formulation for Variant B (minimization of FPR_{sys}) is analogous, with the objective function and detection constraint interchanged.

For the sets of admissible ROC operating points (pairs of detection and false alarm rates) for Varex, Smiths Detection and HALO (denoted by I, J and K with indices i, j and k), the values TPR_{ijk} and FPR_{ijk} are calculated using equations (7) and (8). Using the binary decision variable w_{ijk}, the model selects exactly one combination of operating points for Varex, SD and HALO to maximize objective function under the following constraints:

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(1) false alarm constraint ensuring that the selected configuration does not exceed the allowed system-level false positive rate, (2) capacity constraints of the three automated machines, (3) capacity constraint of human inspection, (4) binary decision constraint.

Objective Function (Variant A – maximize system detection rate)

$$\max\ TPR_{sys} = \max \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\left[d_i^V\, d_j^S\, \left(p_{PI} + d_k^H(1-p_{PI})\right)\right] w_{ijk}$$

(1) False Alarm Constraint

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\left[f_i^V\, f_j^S\, \left(p_{PI} + f_k^H(1-p_{PI})\right)\right] w_{ijk} \le FPR^{max}$$

(2) Machine Capacity Constraints

Varex:

$$\sum_{i,j,k}\left(X\, t_i^V\right) w_{ijk} \le u^V\, T_{avail}^V$$

SD:

$$\sum_{i,j,k}\left(X\left[p d_i^V + (1-p) f_i^V\right] t_j^S\right) w_{ijk} \le u^S\, T_{avail}^S$$

HALO:

$$\sum_{i,j,k}\left(X(1-p_{PI})\left[p d_i^V\, d_j^S + (1-p) f_i^V\, f_j^S\right] t_k^H\right) w_{ijk} \le u^H\, T_{avail}^H$$

(3) Human Inspection Constraint

$$\sum_{i,j,k}\left(X\left[p\, TPR_{ijk} + (1-p)\, FPR_{ijk}\right] t^{HI}\right) w_{ijk} \le u^{HI}\, T_{avail}^{HI}$$

where

$$TPR_{ijk} = d_i^V\, d_j^S\, \left(p_{PI} + d_k^H(1-p_{PI})\right)$$

$$FPR_{ijk} = f_i^V\, f_j^S\, \left(p_{PI} + f_k^H(1-p_{PI})\right)$$

(4) Binary Decision Variable

$$w_{ijk} \in \{0,1\}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{k\in K} w_{ijk} = 1$$

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Figure 4. MILP model of PARSEC system-of-systems configuration

The capacity-related parameters used in constraints (2) include scanning times per parcel, available processing times and maximum allowable utilization levels for Varex, SD and HALO machines, respectively. In constraint (3), the parameters correspond to the available processing time and maximum allowable utilization level of the human inspection stage.

The MILP model was implemented in MATLAB and solved using the Optimization Toolbox (intlinprog solver). The predefined sets of ROC operating points were used to generate the coefficient matrices of the optimization problem, and the resulting mixed-integer linear program was solved to obtain the optimal configuration, which was subsequently used as input to the discrete-event simulation model.

6 Integration of optimization and simulation with discussion

The proposed framework combines analytical modeling, mixed-integer optimization and discrete-event simulation into a unified evaluation approach for the PARSEC system-of-systems architecture.

The MILP model provides an optimal configuration of ROC operating points under static performance assumptions and operational constraints. By precomputing system-level detection and false alarm rates, the optimization efficiently explores all feasible combinations of operating thresholds and selects the configuration that maximizes detection performance (Variant A) or minimizes false alarms (Variant B), while satisfying security and capacity requirements.

However, the MILP model is based on expected values and steady-state assumptions. It does not capture dynamic effects such as queue formation, stochastic variability in parcel arrivals, temporary resource saturation or time-dependent congestion. For this reason, the optimal configuration obtained from the MILP model is subsequently evaluated using the discrete-event simulation model described in Section 3.

The DES model enables assessment of:

- queue lengths and waiting times at individual stages,
- utilization of screening machines under stochastic inflow conditions,
- potential bottlenecks in the resolution lane,
- operational feasibility under peak load scenarios.

This integration ensures that mathematically optimal solutions are also operationally feasible. In particular, near-optimal configurations identified by the MILP model may demonstrate superior dynamic performance when evaluated in the simulation environment, especially under high utilization levels.

The combined optimization–simulation approach thus supports decision-making at two complementary levels:

1. Strategic level, where analytical and optimization models identify suitable operating regions and threshold configurations.
2. Operational level, where simulation validates real-world feasibility and performance under realistic variability.

The analysis confirms that a multi-stage system-of-systems architecture enables greater flexibility in balancing detection performance and inspection workload compared to single-stage configurations. The presence of the P/I shielded branch significantly affects the distribution of workload between HALO and human inspection, emphasizing the importance of explicitly incorporating this effect in both analytical and optimization models.

Due to confidentiality constraints related to system performance characteristics and ROC data, detailed numerical outcomes are not presented in this paper. The emphasis is therefore placed on the modeling framework and its capability to support structured evaluation and configuration of high-throughput parcel screening systems under realistic operational constraints.

7 Conclusion

This paper presented the final system-of-systems architecture of the PARSEC parcel screening concept and its integrated simulation and optimization framework. Following modifications in the technological configuration, including the introduction of computed tomography and the revised hierarchical decision logic, the analytical, simulation and optimization models were adapted to reflect the updated structure.

A probabilistic analytical formulation was developed to describe system-level true positive and false positive rates, explicitly incorporating the P/I shielded branch within the resolution lane. Based on this

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formulation, a mixed-integer linear programming (MILP) model was proposed to select optimal combinations of ROC operating points under security and operational constraints. The optimization model was complemented by a discrete-event simulation model, enabling evaluation of dynamic system behavior, including queue formation, resource utilization and workload distribution.

The combined optimization–simulation approach provides a structured methodology for balancing detection performance and operational feasibility in high-throughput parcel environments. The results demonstrate that the multi-stage system-of-systems architecture offers flexibility in managing the trade-off between detection rate, false alarm rate and inspection workload, particularly under capacity constraints.

In addition to the presented contributions, the developed framework implicitly addresses the following research question: how to systematically determine optimal operating points in a multi-stage parcel screening system-of-systems while balancing detection performance, false alarm rates and operational capacity constraints. The results indicate that the integration of analytical modeling, optimization and simulation provide a viable approach to this problem, enabling both efficient exploration of feasible configurations and validation under realistic operational conditions.

Future work will focus on further extending the proposed framework in several directions. First, a more detailed literature-based benchmarking of alternative system-of-systems screening architectures and optimization approaches could strengthen the comparative positioning of the model. Second, the incorporation of stochastic and time-dependent arrival patterns, as well as adaptive or learning-based threshold selection mechanisms, could enhance the realism of the optimization layer. Third, the integration of quantitative experimental data, including sensitivity analyses and scenario-based evaluation, would enable a more comprehensive validation of the model's robustness and practical applicability. Finally, potential extensions toward real-time decision support systems and digital twin implementations represent a promising avenue for future research and practical deployment.

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