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ADAPTIVE NEUROMODELL BASED ON REAL-TIME DATA OF PASSENGER SERVICE SYSTEMS IN AIRPORTS

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Abstract. *Modern airports operate under increasingly complex conditions, making the effective management of passenger service processes an essential requirement. Traditional static and rule-based control models are generally unable to respond promptly to real-time changes in demand and system workload. As a result, maintaining service quality becomes difficult. These limitations are particularly noticeable during peak periods and unforeseen situations, when long queues form and available resources are not utilized efficiently.*

In this paper, a predictive and self-learning control model for airport service systems is developed. The proposed method considers not only the current queue length but also the dynamics of the system, including the rate of change of queues and waiting times. This allows the controller to estimate near-future conditions and to allocate service resources more appropriately. Furthermore, different operational thresholds are defined for check-in and security control stages in order to reflect the specific characteristics of each process.

The mathematical model is formulated through an objective function with adaptive weighting coefficients and is evaluated using discrete-event simulation. The obtained results indicate that, after a short learning period, the proposed approach re-duces passenger waiting times, improves system stability under heavy traffic, and leads to more efficient use of available resources.

Keywords. *queueing systems, airport operations, real-time control, learning-based methods, predictive resource allocation.*

INTRODUCTION

The theoretical foundations of mass service systems are based on classical queueing theory and are described by stochastic models such as M/M/1, M/M/c [1], [2]. Although these models are effective under stationary conditions, they assume constant arrival and service rates and therefore do not fully reflect time-varying and non-stationary flows. For this reason, their practical application in highly variable fields such as transportation and aviation remains limited [3].

Empirical studies show that passenger flows at airports are unevenly distributed throughout the day, creating periodic peak loads at service points. Static resource planning in this context leads to increased waiting times and reduced operational efficiency [4], [5]. Simulation and analytical models, however, demonstrate that dynamic redistribution of resources yields more effective results [6].

For this purpose, real-time adaptive control methods have been applied, and mechanisms based on queue length and load levels have been proposed [7]–[9]. However, these approaches are mainly reactive and provide delayed decisions.

In recent years, learning-based and reinforcement learning methods have been widely used in optimizing service systems. These methods learn from historical and real-time data to develop more effective control policies in dynamic environments, outperforming classical heuristic methods [10]–[12]. Nevertheless, in existing studies, decisions are mainly based on the current state, while future indicators such as queue growth rate, trend, and predicted waiting time are not sufficiently considered [13], [14].

Therefore, the integration of predictive components remains relevant. The proposed work presents an intelligent control model that learns and predicts, incorporating queue dynamics speed and trend indicators into the decision-making mechanism.

Problem Statement

It is required to develop a self-learning neuromodel based on a predictive and adaptive model for airport service systems.

Solution Method

The airport mass service system is considered to consist of two main stages:

- Check-in service,
- Security screening.

For the service system of both stages, the following adaptive objective function is adopted:

$$\begin{cases} J(t) = \alpha(t)\,\bar{W}(t) + \beta(t)\,\bar{L}(t) + \gamma(t)\,C(t) \to min \\ \alpha(t) + \beta(t) + \gamma(t) = 1 \end{cases} \tag{1}$$

Where:

$\bar{W}(t)$– average waiting time,

$\bar{L}(t)$– average queue length,

$C(t)$– number of active service resources,,

$\alpha(t), \beta(t), \gamma(t)$– positive real-time weighting coefficients.

J(t) — is the overall “cost/performance/quality” indicator of the system.

Minimizing this quality indicator represents the optimal state of the service system. The adaptiveness of the weighting coefficients allows dynamic adjustment of system priorities over time, fundamentally differing from classical fixed-weight models [1], [14]. For a small time interval Δt, the rates of change of $\bar{W}(t)$,$\bar{L}(t)$, və $C(t)$ pare calculated:

$$v(t) = \frac{L(t)-L(t-\Delta t)}{\Delta t}, \text{ queue rate}$$
$$\tau(t) = \frac{\bar{W}(t)-\bar{W}(t-\Delta t)}{\Delta t}, \text{ waiting gradient}$$
$$\Delta C(t) = \frac{C(t)-C(t-\Delta t)}{\Delta t} \text{- change in active service resources}$$

Where

Δt s a small time interval, usually 1-2 minutes.

During Δt the weighting coefficients remain constant.

The queue rate v(t) allows the system to understand the dynamics of queue growth or shrinkage. If $v(t) > 0$ the queue is growing – i.e., the number of arriving passengers exceeds those being served. If $v(t) < 0$ the queue is shrinking and the system gradually returns to normal. The value of $v(t)$indicates the intensity of this change. For example, $v(t) = +3 \text{ passengers/min}$ means that 3 passengers are added to the queue every minute.

The waiting gradient τ(t) reflects how service quality changes over time. If $\tau(t) > 0$, waiting times increase and the situation worsens, signaling that the system needs reorganization. Conversely, if τ(t) < 0, the situation improves and the system self-stabilizes.

The combined use of these parameters allows the system to predict not only the current state but also the near-future behavior.

1. **Learning-based decision mechanism:** The decision mechanism is expressed as a functional dependent on the specified parameters:

$$f_\theta : (v(t), \tau(t), \Delta C(t)) \to \Delta J(t), \tag{2}$$

This function is implemented using a neural model. In our application, a simple but effective multilayer perceptron (MLP) was used. The network structure is as follows:

- **Input layer:** 3 neurons (accepting ($\Delta C(t)$, v, τ parameters)
- **Hidden layer 1:** 16 neurons (ReLU activation function applied)
- **Hidden layer 2:** 8 neurons (ReLU activation function applied)
- **Output layer:** 1 neuron (linear activation function, outputting ΔJ)

The learning process is built in the simulation environment based on minimizing the objective function J(t). At each time step, the system observes the state, makes a decision, and evaluates the result using waiting time, queue length, and resource usage indicators. Parameters are adaptively updated following the reinforcement learning principle, while supervised learning elements are integrated via benchmark decisions [11].

Optimization is performed using stochastic gradient descent (SGD) and the Adam algorithms [19], [20]. Learning rate decay ensures convergence. Training was carried out over 500–1000 episodes (each representing an 8-hour operational cycle). Unlike systems based on predefined rules, the learning-based approach automatically forms strategies based on experience and provides adaptive adjustment to a dynamic environment.

The model was evaluated in a discrete-event simulation environment [14], [18]. The terminal was modeled as a multi-stage service system, taking into account non-stationary passenger flows, peak loads, and resource constraints. Static, reactive, and predictive learning-based strategies were compared in terms of average waiting time, queue length, and resource utilization. The interface provides real-time monitoring and decision support.

RESULTS AND DISCUSSION

The effectiveness of the proposed predictive-adaptive model was evaluated in a comparative manner against a static control approach based on discrete-event simulation results. The main performance indicators analyzed were average waiting time, queue length, and the number of active resources.

İntellektual Hava Limanı Növbə İdarəetmə Sistemi

Cari Göstəricilər

Check-in Növbəsi	Təhlükəsizlik Növbəsi	Check-in Aktiv Resurs	Security Aktiv Resurs
2057	0	12	2

AI Qərarları (İzahlı)

23:41:16 — Check-in → +1 köşk açıldı
Səbəb: Artan növbə

23:41:16 — Check-in → +1 köşk açıldı
Səbəb: Artan növbə

23:41:16 — Check-in → +1 köşk açıldı
Səbəb: Artan növbə

23:41:16 — Check-in → +1 köşk açıldı
Səbəb: Artan növbə

23:41:16 — Check-in → +1 köşk açıldı
Səbəb: Artan növbə

Figure 1. User interface of the intelligent airport queue management system operating based on real-time simulation.

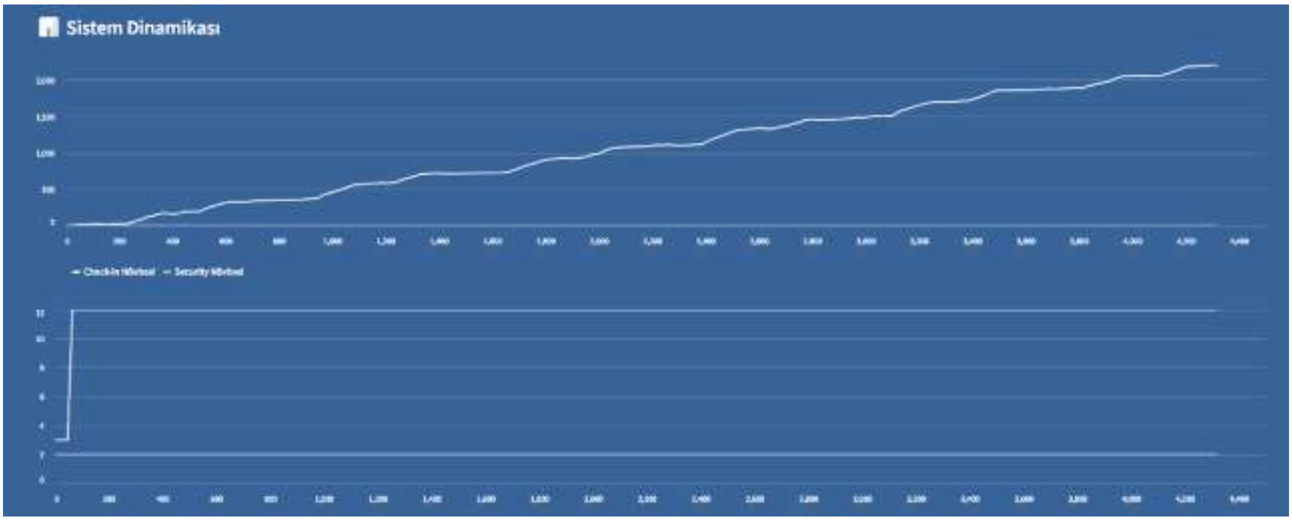

Figure 2. Temporal dynamics of queue lengths and active resources at check-in and security stages under the predictive learning-based control model.

Figure 2 presents the system's dynamic behavior over the simulation period. As shown in the graphs, at the check-in stage, the increase in passenger flow (top graph) is compensated by timely resource augmentation by the AI (middle graph). At the security stage, under low-load conditions, resources are maintained at a minimal level (bottom graph). These results confirm the stage-specific and differential control strategy of the model.

Comparison of average waiting time

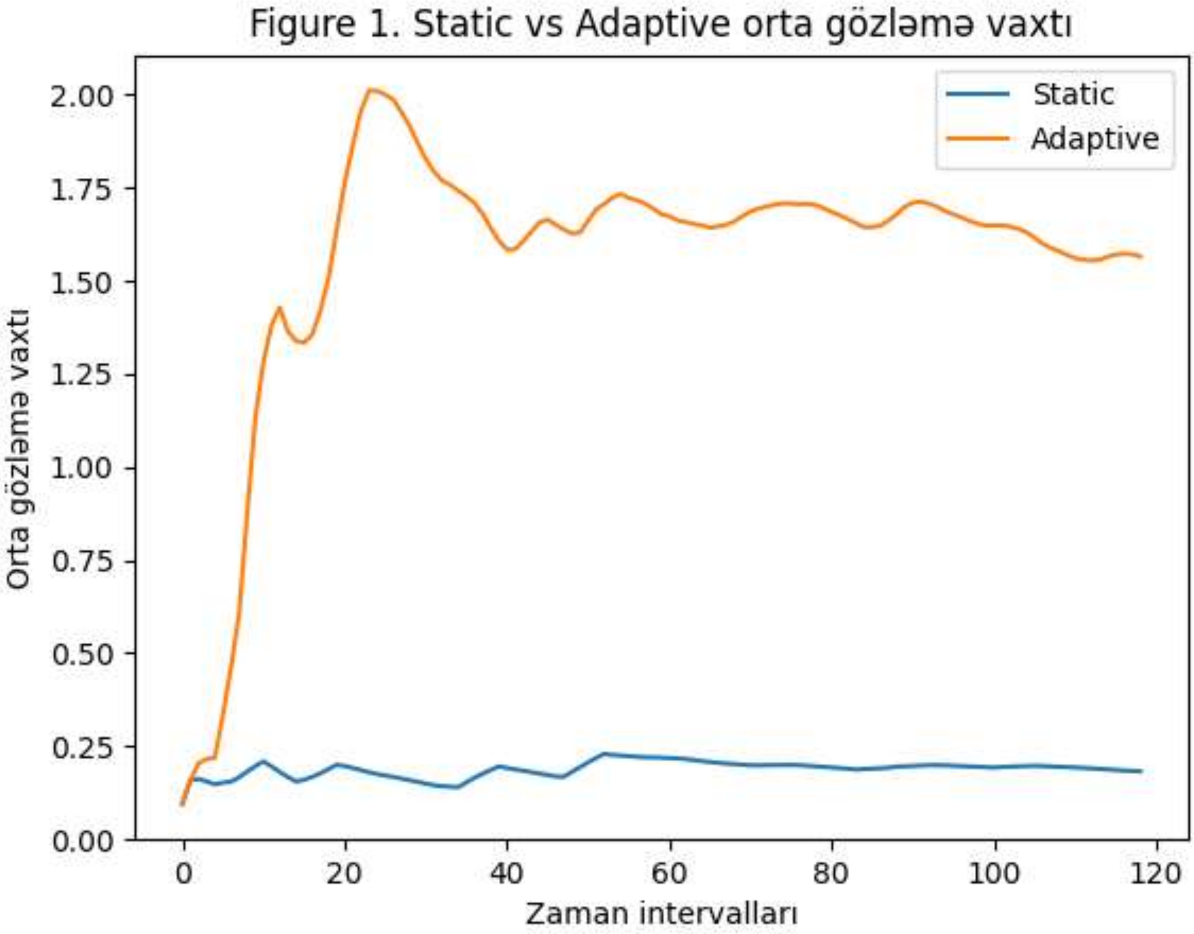

Figure 3. Static vs Adaptive average waiting time

Figure 3 shows the temporal change of average waiting time for static and adaptive models. The relative increase observed in the initial stage of the adaptive model is associated with the learning process. However, once the learning phase is completed (approximately after interval 40), the indicators stabilize, and the system demonstrates more robust behavior under non-stationary flow conditions. This indicates that the adaptive approach maintains service quality in the long term.

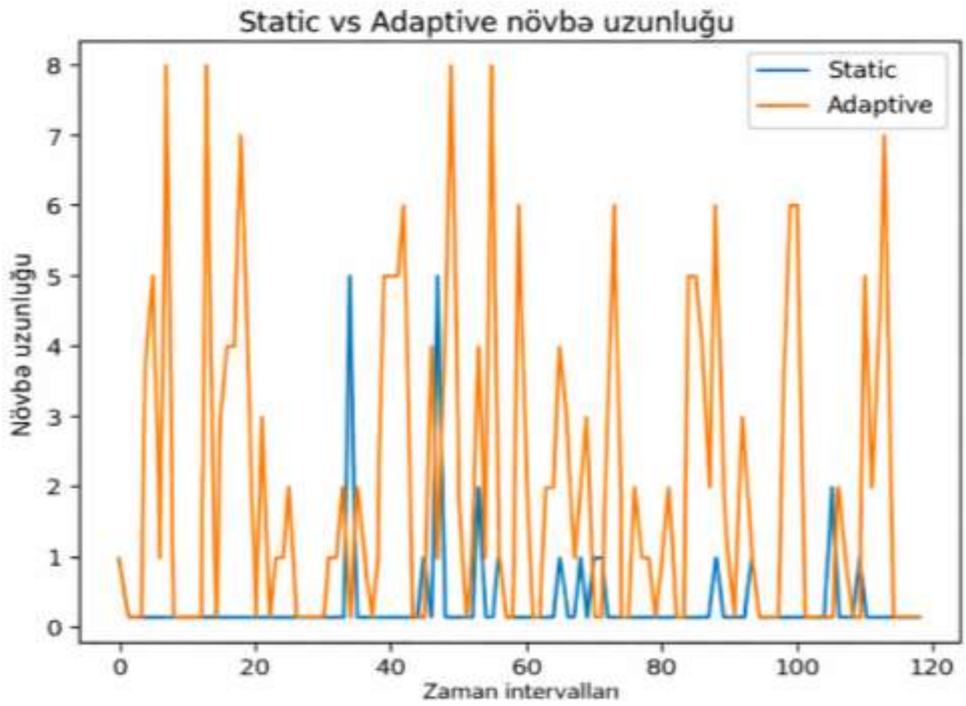

Figure 4. Static vs Adaptive queue length

Figure 4 shows that higher fluctuations in queue length are observed in the adaptive model. These fluctuations are a result of real-time adjustments and prevent system collapse during peak load intervals.

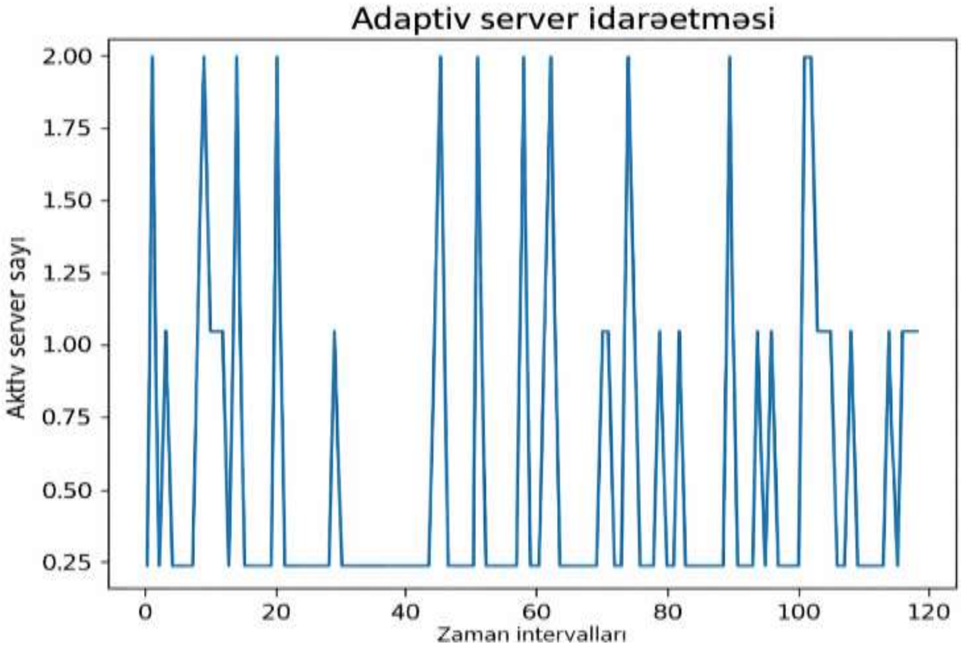

Figure 5. Adaptive service management

Figure 5 shows the dynamic change in the number of active service resources. This behavior ensures efficient use of resources and allows the system to flexibly adapt to real-time conditions.

In this work, a predictive and learning-based intelligent approach has been proposed for the effective management of airport mass service systems in non-stationary and dynamic operational environments. The proposed model, based on real-time operational data, considers not only the current state but also the rate of change of queue dynamics and the trend of waiting time, which allows preventive and more rational allocation of resources. Discrete-event simulation results have shown that the approach provides higher performance compared to traditional static and reactive methods in terms of reducing waiting times, maintaining system stability during peak loads, and optimizing resource usage.

The main scientific innovations of the study are as follows:

1. Development of a predictive real-time decision mechanism based on queue rate and waiting time trend;
2. Formation of a mathematical model with an extended objective function using adaptive weighting coefficients;
3. Application of an aviation-specific differential control strategy considering the characteristics of airport stages;
4. Proposal of the presented methodology as a general and exportable framework applicable to other large-scale service and transportation systems.

It should be noted that the proposed approach can be considered promising not only for aviation terminals but also for railway stations, ports, urban transport hubs, and other multi-flow service systems.

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