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Multi-Objective Optimization for MOBA Matchmaking Using NSGA-II: A Review of Queueing-Based Modeling and a Modeling – Optimization – Evaluation Framework

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ABSTRACT
Massively multiplayer online battle arena (MOBA) matchmaking requires long-term trade-offs among fairness, waiting time, and system efficiency. Recent studies formulate matchmaking as a queueing and dynamic matching problem, and incorporate globally optimized sequential decision-making and engagement-oriented objectives to capture long-run outcomes; meanwhile, multi-objective evolutionary algorithms, represented by NSGA-II, characterize inherent objective conflicts through Pareto solution sets and provide interpretable trade-off options for policy selection. This review is organized around a three-layer "modeling-optimization-evaluation" framework: it summarizes computable modeling components from queueing theory and dynamic matching, synthesizes how NSGA-II encodes matchmaking policy parameters and handles operational constraints, and consolidates offline performance metrics together with quality indicators for evaluating Pareto sets.

KEYWORDS
MOBA matchmaking; queueing theory; NSGA-II; Multi-objective optimization; Pareto front

1 Introduction

1.1 Research Background and Problem Definition

The MOBA (Multiplayer Online Battle Arena) matchmaking system can be abstracted as an online service process involving "random arrival—queue waiting—batch match formation": player arrival exhibits randomness and time-varying characteristics, while match formation requires satisfying team size constraints (e.g., 5v5), as well as segmentation/region/team-up and role constraints. Matching quality is typically characterized by three metrics: fairness (skill balance, win probability equilibrium, role satisfaction, and controllable teaming advantages), waiting experience (mean and long-tail wait times, timeouts, and abandonment rates), and system efficiency (throughput, stability, and cross-region network costs). These objectives are mutually constrained in online environments, creating measurable trade-offs between rule relaxation and quality assurance that vary with tier and load.

1.2 Overview Objectives and Significance

Industrial systems often employ heuristic thresholds and relaxation curves for parameter tuning, yet struggle to uniformly characterize the boundary between "waiting costs and fairness gains" and establish transferable metric feedback loops. Related research advances along two distinct paths: First, queueing theory and dynamic matching models quantify the relationship between queue states, rule parameters, and the trade-off between waiting and fairness. Second, global sequence optimization and engagement objectives elevate matching to a cross-period planning problem, expanding strategy evaluation from single-episode quality to long-term gains [1-2]. In MOBA scenarios with pronounced multi-objective conflicts, NSGA-II can generate a set of Pareto solutions covering diverse preference trade-offs through a single computation, providing operations teams with interpretable compromise spaces [3]. Building upon this, this review systematically organizes key objects, algorithm adaptation, and metric systems around the "modeling-solving-evaluation" framework to establish a reusable analytical framework and consistent terminology.

2 Literature Review

2.1 Queueing Theory and Rule Design Perspective

The queueing framework decomposes rule design into decisions such as "when to start the game," "how to allocate pools," and "when to relax restrictions." It characterizes the mapping relationship between waiting time and rule parameters through analytical or simulation methods, providing a basis for structured rule design [1].

2.2 Dynamic Matching and Team Competition Modeling

Team competition scenarios can be modeled as dynamic matching: the system constructs two teams based on player sequence arrival, establishing long-term objectives through skill gap penalties and waiting costs, thereby deriving structured online decision forms [2].

2.3 Global Sequence Optimization and Engagement-Oriented Objectives

Global optimization research formulates matching as a planning problem requiring determination of the "matching sequence," proposing scalable online implementation frameworks. Engagement-oriented studies further incorporate player retention/participation into objectives, forming modeling approaches more aligned with operational metrics [4-5].

2.4 Multi-Objective Evolutionary Optimization and Solution Set Evaluation

NSGA-II maintains solution set diversity through non-domination ordering, crowding distance, and elite retention, commonly used to output Pareto solutions and support multi-preference selection. Metrics like hypervolume evaluate solution set coverage and approximation, serving as unified comparison tools across different optimization settings [3,6].

2.5 Re-Matching and Multidimensional Fairness in MOBA

The re-matching framework reoptimizes candidate assignments before final allocation to jointly address skill fairness and position satisfaction. It provides corresponding system implementations and evaluation protocols, highlighting that fairness requires computable expressions of multidimensional signals and actionable constraint interfaces [7].

3 Research Content

3.1 Scope and Problem Decomposition

This review centers on "multi-objective optimization in MOBA matchmaking," decomposing research elements into three layers: modeling (computable expressions of states, constraints, and objectives), solving (candidate strategy generation mechanisms under multi-objective conflicts), and evaluation (offline metrics and solution set quality measures). These layers are interconnected through unified variables, metrics, and strategy parameter interfaces to organize literature and align research descriptions.

3.2 Literature Search and Screening Process

The search scope covers English-language open literature from 2021 to 2025. Search themes are formed by three sets of keywords: matchmaking/online games/MOBA/queueing/dynamic matching, multi-objective optimization/NSGA-II/Pareto, and engagement/fairness/position satisfaction. Sources include ACM Digital Library, IEEE Xplore, SpringerLink, and ScienceDirect. Screening employs a two-tiered approach: first, excluding studies lacking online matching or model/algorithm components based on titles and abstracts; subsequently retaining full-text articles explicitly specifying decision variables (or strategy parameters), objective criteria, and evaluation metrics (or protocols). For conference and journal versions of the same study, the version with more complete information was prioritized. Citation tracing was used to supplement related work on the same topic, forming a core literature set for subsequent coding.

3.3 Information Extraction and Coding Rules

To establish comparability, information extraction employs a structured coding table to record: application scenarios, arrival and queueing assumptions, state variables, constraint sets, objective sets, solution methods, and evaluation protocols. During coding, synonymous terms were normalized: for instance, fairness at the operational level was mapped to skill gap loss, win rate deviation loss, or position mismatch penalty, with consistent metric definitions. Waiting-related metrics were uniformly recorded as mean, quantiles, timeout ratio, and abandonment rate to align reporting across studies. For studies involving multi-objective optimization, additional documentation includes objective vector dimensions, objective scaling normalization methods, and constraint handling strategies to align with NSGA-II mechanisms.

3.4 Modeling Layer: Queue Abstraction and Target Interface Construction

The modeling layer uniformly adopts the abstraction of "random arrival + hierarchical queues + batch service": Players arriving enter a queue pool, and the system selects 2n players to form a game session and exit the system when constraints are satisfied. Queue segmentation is expressed in the code as "decomposable dimensions," including rank/tier, geographic region, party size, and preferred position. Correspondingly, the state vector must contain at least: sub-queue lengths, wait-time statistics, position supply/demand signals, and policy relaxation thresholds. The target interface layer decomposes fairness into computable loss terms: skill disparity loss can be represented by mean difference, variance difference, or distribution distance between teams; position satisfaction loss can be expressed via preference-unmet penalties or dual metrics of fulfillment rates; Environmental bias introduces correction terms via factors like faction/map, manifesting as offsets or additional penalties in win rate objectives. Waiting objectives are represented by distribution statistics and linked to behavioral metrics like timeout rates and abandonment rates to characterize the impact of long-tail waits on experience, where abandonment behavior can be modeled by patience time (reneging) distributions [1-2,7-8]. The arrival process is encoded to indicate whether it is modeled as Poisson, non-homogeneous arrivals, or segmented empirical distribution. Relaxation mechanisms are recorded as feasible sets or threshold functions varying with waiting time, used to map online rules into computable constraint changes.

3.5 Solution Layer: NSGA-II Adaptation and Strategy Parameter Encoding

The Solution Layer transforms per-game matching decisions into a strategy parameter search problem to generate an offline candidate strategy library for on-site selection. Encoded objects include: relaxation curves for segment difference thresholds varying with waiting time, pool splitting/merging rules, position constraint strength (hard constraints or soft penalty weights), cross-region/delay thresholds, timeout fallback rules, and abandonment penalty weights. NSGA-II represents each individual as a set of strategy parameters. Through non-dominated sorting and crowding distance, it generates a non-dominated solution set covering different trade-off orientations [3]. In the process log, individual evaluation obtains the objective vector by calling the evaluation layer interface, followed by sorting and elite update. Outputs are presented as a Pareto frontier approximate solution set and its parameter configuration table, facilitating linkage with evaluation layer metrics. Constraint handling is categorized into penalty function methods and feasibility-priority rules within the codebook, documenting implementation details during sorting and selection phases. For hard role combination constraints or delay upper-bound constraints, usage of feasibility repair strategies is additionally recorded.

3.6 Evaluation Layer: Offline Metrics Framework and Solution Set Quality Metrics

The evaluation layer is organized into three metric groups: Waiting Experience (mean, P95/P99, timeout ratio, abandonment rate), Fairness (skill gap statistics, win rate deviation, role fulfillment rate, team composition profiling), and System Efficiency (matches per unit time, cross-region costs, resource utilization and stability metrics). Data sources are categorized in the coding table as internal logs versus public match logs (e.g., Dota2), with available fields documented for metric calculation standards. Metric computation may utilize historical log replays or queue simulations, incorporating policy parameters as inputs to generate comparable offline evaluation outputs. For cross-period policies, the evaluation protocol records time window length, warm-start methods, and peak-valley tiered reporting formats in the coding table. For solution sets generated by multi-objective optimization, unified metrics like hypervolume are applied to enable comparative evaluation across different sets, with implementation details such as reference point selection, objective normalization, and sampling strategies documented [6]. Online deployment evaluations are recorded via release comparison and metric monitoring protocols [4,7]. Metric statistics are coded to distinguish between aggregate and segmented scopes, with time granularity and segmentation granularity (level/region/team size) documented. For hypervolume calculations, the coding table records reference point sources and normalization steps to ensure comparability across different configurations.

3.7 Output Organization and Reproducibility Elements

Output organization follows a three-tier framework: modeling layer variables and target interfaces, solution layer algorithmic mechanisms and parameter encoding templates, and evaluation layer metric dictionaries and solution set quality measurement methods. Reproducibility elements include a glossary of terms/symbols and a structured summary following the format "Model Assumptions—Decision Variables—Objective Set—Evaluation Protocol." This structure fixes mapping relationships across studies and supports subsequent comparative analysis. Additionally, the notation systems and variable definitions used in each literature source are documented and uniformly replaced with consistent symbolic

conventions throughout the review to minimize ambiguity during cross-document comparisons.

4 Summary

4.1 Key Review Findings

Analysis based on the "modeling-solving-evaluation" framework reveals that MOBA matchmaking can be consistently formulated as multi-objective decision-making on an online queueing system. The modeling layer must provide computable state representations and interfaces for multidimensional fairness signals; The solution layer can generate a Pareto solution library within the policy parameter space using NSGA-II to cover diverse trade-offs between waiting time, fairness, and efficiency; the evaluation layer requires an offline metric system comprising waiting distribution, skill balance, role satisfaction, and efficiency indicators, while using collective metrics like hypervolume to characterize solution set quality, thereby supporting policy comparison and selection [3,6].

4.2 Practical Implications and Future Research Directions

For engineering implementation, multi-objective optimization can be applied to build offline policy libraries, combined with real-time queue state for online policy switching; At the metric framework level, long-tail waiting and abandonment behaviors must be explicitly represented in objectives and evaluations to prevent mean metrics from obscuring experiential disparities. Fairness can be expanded from single-skill gaps to a joint characterization of "skill-location-team structure," forming a composable modeling interface with global sequence optimization and engagement objectives [2-3,7].

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