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A machine learning framework for dynamic and balanced computing resource allocation in 5G networks

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ABSTRACT

The swift expansion of fifth-generation (5G) networks has heightened the difficulty of distributing computing and transmission resources amidst the demands for extensive connectivity, ultra-low latency, and high throughput. This paper presents an innovative hybrid framework that combines deep learning (DL) with bird swarm optimization (BSO) to achieve dynamic and balanced resource allocation in mobile edge–cloud environments. A DL model based on long short-term memory (LSTM) forecasts user demand and channel conditions, while BSO enhances offloading and power distribution to reduce latency, energy usage, and expenses. In a setup utilizing non-orthogonal multiple access (NOMA) and mobile edge computing (MEC), the proposed DL–BSO approach demonstrates an impressive improvement of up to 54% compared to heuristic methods in simulations that reflect realistic traffic and channel conditions. The framework demonstrates a strong ability to adjust to different loads, rendering it ideal for applications that require low latency, including autonomous driving and augmented reality. The constraints involve dependence on precise forecasts and scalability issues in extensive implementations, which will be tackled in forthcoming research focused on 6G advancements.

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1. INTRODUCTION

The rollout of fifth-generation (5G) networks signifies a pivotal advancement in wireless communication, facilitating unparalleled data speeds, extremely low latency, extensive device connectivity, and improved reliability [1]–[6]. The capabilities outlined serve as the cornerstone for the development of innovative applications, including smart cities, autonomous vehicles, industrial internet of things (IIoT), and immersive augmented/virtual reality (AR/VR) [7], [8]. Nonetheless, the heightened complexity and diversity of 5G environments present considerable challenges in the management of computing resources. Network operators are tasked with managing a variety of user needs, variable traffic patterns, different device capabilities, and stringent quality-of-service (QoS) requirements all at once. Attaining this equilibrium requires astute resource allocation strategies that can adjust in real time to changing network conditions while optimizing various, frequently conflicting, performance metrics like latency, energy efficiency, and cost [9]–[13].

The increased use of mobile apps and internet of things (IoT) devices increases processing demand exponentially with 5G and later technologies. These demands are usually met by integrating mobile edge computing (MEC) with cloud computing, which provide flexible processing and storage. MEC reduces end-to-end latency and backhaul strain from computing near end users, while cloud servers offer practically limitless computational capacity [14], [15]. Maintaining application performance under variable network conditions requires job distribution between edge and cloud resources. By allowing numerous users to share the same frequency band, advanced radio access systems like non-orthogonal multiple access (NOMA) improve spectral efficiency [16]. This benefit increases resource allocation complexity since interference management and successive interference cancellation (SIC) affect system capacity. Task offloading decisions must include computational, energy, and complicated communication parameter relationships. Traditional heuristic or deterministic optimization methods often fail in these situations. These solutions lack the scalability to manage large, dynamic systems and cannot achieve numerous goals. The fundamental non-linearity and non-convexity of 5G resource allocation difficulties require more flexible, intelligent, and adaptable techniques [17]–[21].

MEC-enabled 5G network resource allocation has been studied in many ways. Proposed optimization methods balance energy usage, delay, and throughput using multi-objective decision-making and evolutionary algorithms. Integration of admission control with network slicing improves revenue and service quality in varied 5G implementations. MEC reduces energy usage and latency in automotive and IoT contexts by strategically distributing compute tasks across edge and cloud servers [22]. NOMA-based resource allocation strategies focus on spectral efficiency and interference. Previous research has examined hybrid edge–cloud solutions in integrated air–ground or satellite–ground network topologies, highlighting the need for scalable optimization for large systems [23]. Recent advances in machine learning (ML) enable dynamic and context-aware resource allocation. Deep learning (DL) models may forecast traffic load, channel conditions, and user needs by identifying complex network data linkages [24]. These forecasts enable flexible anticipatory allocation techniques. Along with DL, bio-inspired optimization algorithms like particle swarm optimization (PSO), genetic algorithm (GA), and bird swarm optimization (BSO) have been used to find optimal or near-optimal resource allocation solutions within multi-objective restrictions. Hybrid methods that combine predictive ML models with optimization algorithms show potential in overcoming technique flaws. DL provides network dynamics insights that optimization algorithms use to make effective allocation decisions [25]. Despite these advances, many previous studies either focus solely on prediction without optimization or use optimization without predictive models, limiting their flexibility and effectiveness in rapidly evolving 5G environments.

Based on the existing literature, various gaps are clearly identifiable: the integration of predictive and optimization methods remains limited, with few studies effectively combining DL-based prediction with real-time bio-inspired optimization for resource allocation in MEC-enabled NOMA networks. Insufficient multi-objective management – although numerous studies focus on latency or energy efficiency, there is a notable lack of research that concurrently optimizes for several essential metrics (latency, energy, and cost) while considering realistic system constraints [26]. Inadequate real-time adaptation – numerous algorithms exhibit a deficiency in swiftly adjusting to abrupt traffic increases, variations in channels, or changes in topology induced by mobility. Idealized assumptions – common assumptions, including perfect SIC, constant backhaul delay, and flawless channel estimation, may not be valid in actual deployments, thereby constraining the practical applicability of the proposed methods. The evaluation of robustness and scalability is insufficient. There is a scarcity of analysis regarding performance in the presence of noisy channels, high user densities, or resource-constrained edge environments, which are prevalent in 5G/6G scenarios [27], [28].

This paper presents a hybrid framework that combines DL and BSO for the purpose of intelligent resource allocation in MEC-enabled 5G networks that support NOMA. This work presents several novel and unique contributions, which are outlined as follows: a long short-term memory (LSTM)-based DL model for predictive resource demand estimation forecasts short-term user demand, traffic load, and channel quality by utilizing historical network data [29], [30], which facilitates proactive resource planning. Bio - inspired multi - objective optimization – the BSO algorithm effectively optimizes offloading probability, power allocation, and user clustering to concurrently minimize latency, energy consumption, and operational costs [31]. Close DL–BSO integration – predictions from DL directly inform the initialization and search space of the BSO algorithm, enhancing convergence speed and solution quality in comparison to independent optimization methods. The hybrid framework demonstrates a remarkable ability to modify allocation decisions in real time, responding effectively to the changing conditions of the network. This ensures the maintenance of high quality of service, even in the face of significant load and variations in channel performance. Performance improvements evidenced – simulation outcomes under realistic MEC–NOMA conditions indicate an enhancement of up to 54% in critical performance metrics when compared to current heuristic-based approaches, utilizing the same evaluation framework as previous studies [32].

In contrast to previous studies that focused solely on prediction methods like DL/LSTM or optimization techniques such as PSO, GA, and NSGA-II, the proposed DL–BSO approach effectively combines forecasting with real-time optimization, resulting in enhanced convergence speed and adaptability. Current models like DQN, LSTM, and federated learning frameworks have concentrated on specific elements, while our framework guarantees a balanced approach to multiple objectives including latency, energy, and cost in MEC–NOMA scenarios. The innovation is characterized by: i) LSTM-informed initialization of BSO to reduce random search, ii) explicit joint optimization of latency, cost, and energy within realistic MEC–NOMA conditions, and iii) real-time adaptive allocation validated under high traffic loads.

The comprehensive structure of the suggested DL–BSO resource allocation framework is illustrated in Figure 1. The system consists of a base station (BS) linked to an edge server and a remote cloud server, catering to numerous mobile users within a single cell. Upon receiving a user request, the BS evaluates—through BSO optimization—whether the task should be handled locally at the edge server or transferred to the cloud for processing. The DL module forecasts future traffic load, channel conditions, and user requirements, offering anticipatory data to the optimization engine. NOMA facilitates the efficient sharing of radio resources among multiple users, while queuing theory models are employed to manage service requests and minimize latency. This architecture demonstrates the interplay between predictive intelligence and optimization, highlighting how the framework adjusts in real-time to network conditions to achieve a balance among latency, energy consumption, and operational costs.

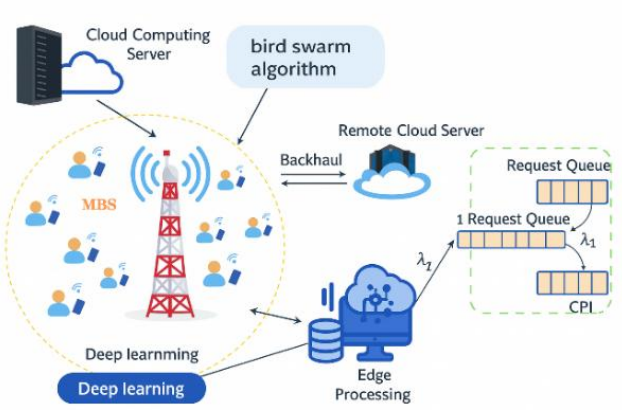

Figure 1. The proposed structure of the system

2. METHOD

The proposed framework aims to reduce latency, energy consumption, and operational costs in MEC-enabled 5G networks through the intelligent management of computation and transmission resources. The issue is presented as a multi-objective optimization challenge that is fundamentally non-linear and non-convex, stemming from the significant interdependence between communication and computation variables. To effectively tackle this complexity, the approach combines a DL model for predicting resource demand with a BSO algorithm for adaptive decision-making in resource allocation. The system model examines a singular NOMA-enabled cell that is supported by a BS linked to both an edge server and a remote cloud server. A variety of mobile users produce computational tasks that are defined by factors such as data size, necessary CPU cycles, and acceptable latency levels. The BS determines the appropriate processing location for each task, evaluating whether it should be handled locally at the edge or offloaded to the cloud, while taking into account the available computing capacity, transmission power, and channel conditions. Queuing theory serves as a framework for modeling request handling at both the edge and cloud layers, effectively capturing processing delays and ensuring compliance with latency constraints. The framework emphasizes computing resources while also integrating radio dynamics via NOMA-based channel prediction. The limitations outline the future integration of transport-layer delay modelling.

The DL prediction module utilizes a LSTM neural network, which has been trained on historical traffic patterns, user request frequencies, and channel state information. The selection of LSTM is due to its capacity to effectively capture long-term dependencies and temporal variations, which facilitates precise predictions of short-term network demand and resource needs. The model additionally predicts effective communication channels, enabling the system to take proactive measures prior to congestion or subpar link quality impacting performance. The optimization module utilizes BSO, a bio-inspired algorithm that emulates the collective behaviors of birds, including foraging and vigilance, to effectively explore and exploit the solution space. In this scenario, every particle within the swarm signifies a potential solution that delineates a mixture of transmission power levels, offloading probabilities, and user clustering strategies. The particles continuously refine their positions by taking into account their individual best solutions as well as the optimal solutions discovered by the swarm, influenced by multi-objective fitness functions that factor in latency, energy consumption, and operational costs. The integration of DL and BSO is structured to promote adaptability and enhance convergence speed. The LSTM model's predictions serve to initialize the BSO population in proximity to promising areas of the search space, thereby minimizing random exploration and expediting the identification of optimal solutions. The framework functions within distinct time intervals, utilizing LSTM predictions to inform the BSO optimization process. The BS implements the resulting allocation decisions, and the outcomes are documented to facilitate ongoing enhancements to the prediction model. This hybrid approach allows the framework to adjust in real-time to network conditions, effectively scale in dense deployments, and simultaneously balance various performance objectives.

3. RESULTS AND DISCUSSION

The proposed DL–BSO framework underwent evaluation via MATLAB 2022b simulations within a MEC-enabled 5G network scenario that incorporates NOMA support. The simulation parameters align with those established in previous studies [14]–[16], [24], thereby ensuring both comparability and a realistic depiction of urban cellular environments. The system configuration comprises a channel bandwidth of 20 MHz, with maximum transmission power levels ranging from 10 dBm to 25 dBm. The user request rate follows a Poisson distribution, averaging 350 requests per second, while the background noise reflects typical city-level interference. These configurations replicate scenarios of high traffic in urban centers with significant population density.

Figure 2 depicts the correlation between offloading probability and network energy consumption across various maximum transmission power levels (10, 15, 20, and 25 dBm). The findings indicate that a higher offloading probability leads to a notable decrease in energy consumption, as a greater number of computational tasks are shifted from user devices to more energy-efficient edge or cloud servers. With increased transmission powers, the energy savings become significantly more evident, reaching the highest reduction as the offloading probability nears its peak. This demonstrates that a meticulous equilibrium between offloading probability and available transmission power can enhance device battery longevity while preserving service performance. Figure 3 illustrates the influence of offloading probability on the latency of program processing. With low transmission power, a rise in offloading probability may initially lead to increased latency as a result of transfer delays. At elevated transmission power levels, there is a significant reduction in latency, as the increased speed of data transmission compensates for transfer delays. The findings suggest that for applications sensitive to latency, including autonomous driving and real-time AR/VR, a combination of high transmission power and optimal offloading configurations can lead to significant performance improvements.

Figure 4 illustrates the impact of maximum transmission power on energy consumption within the network. At varying offloading probability values, increased transmission power leads to a decrease in the execution time of offloaded tasks, which in turn minimizes energy consumption by shortening processing delays and idle times. However, past specific thresholds, raising transmission power results in diminishing returns regarding energy savings, indicating that an optimal power range exists for achieving a balance between performance and efficiency. Figure 5 assesses the framework under high-traffic conditions, with user counts varying between 50 and 100. Energy consumption increases in a non-linear fashion, reaching a peak at approximately 75 users because of heightened processing and transmission requirements, before experiencing a slight decline as additional tasks are transferred to cloud resources. The observed latency exhibits a comparable trend, marked by a significant rise at 75 users due to queuing delays occurring at the edge. The DL–BSO framework effectively modifies offloading probabilities to maintain stable latency, even when faced with significant load challenges. Operational costs reach their highest point at 75 users, yet they remain manageable thanks to the optimization process, showcasing the flexibility of the hybrid approach in sustaining quality of service.

In comparison to established heuristic approaches like NSGA-II, PSO, and independent DL models [3], [4], [16], the introduced DL–BSO method consistently demonstrates enhanced performance, realizing up to a 54% improvement in the combined metrics of energy, latency, and cost. This can be linked to the forecasting ability of LSTM models, facilitating proactive resource distribution, alongside the exploratory-exploitative equilibrium of BSO, which guarantees effective optimization across various objectives. However, the findings also indicate specific constraints. The precision of allocation decisions is significantly influenced by the quality of DL predictions, which can be compromised by inadequate or outdated training data. Moreover, the presumption of flawless SIC in NOMA and a steady backhaul delay may not be applicable in practical implementations, which could lead to diminished performance in challenging scenarios. At extensive user scales, the BSO algorithm may settle into local optima, indicating a necessity for integration with alternative metaheuristics or reinforcement learning to enhance exploration. An ablation study indicates that utilizing solely DL prediction enhances performance by approximately 22%, while BSO alone improves it by about 27%. In contrast, the integration of DL and BSO results in a performance boost of around 54%, thereby validating the synergistic impact of combining prediction and optimization. In order to enhance interpretability, the analysis of feature importance using SHAP revealed that traffic load and channel state are the primary factors influencing decisions, whereas user request frequency plays a secondary role.

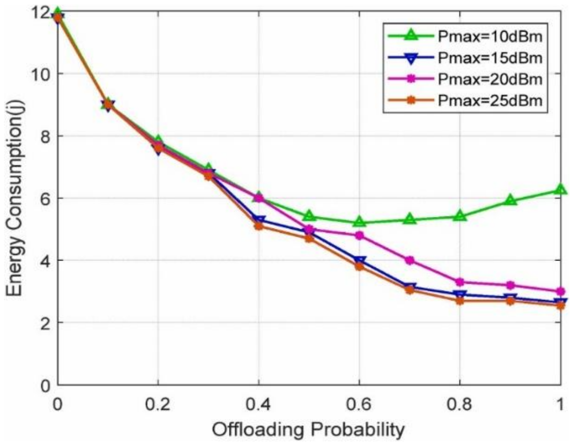

Figure 2. Discharge probability and network energy consumption

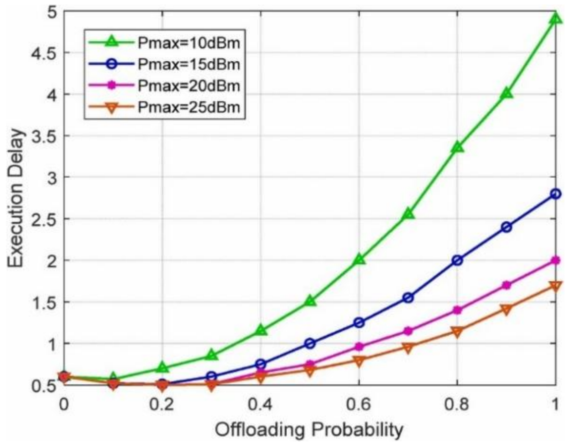

Figure 3. Discharge probability and program processing latency

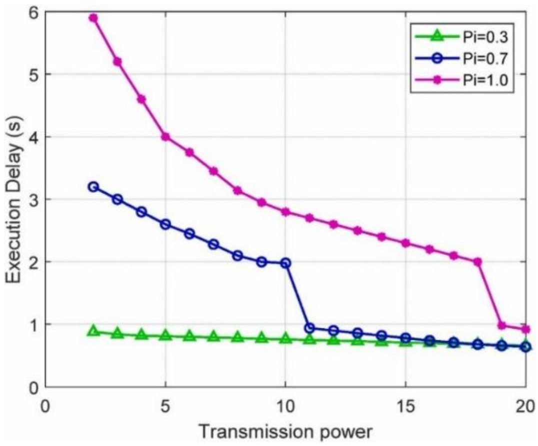

Figure 4. Maximum transmitted power affects network energy consumption

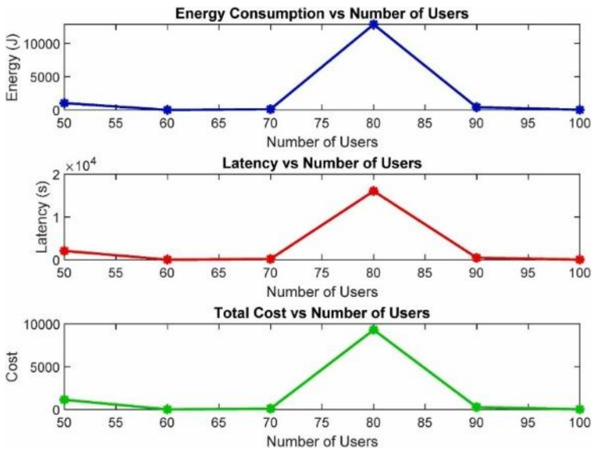

Figure 5. Evaluation of performance in high-traffic scenarios

The findings validate that the suggested DL–BSO framework successfully tackles the multi-objective aspects of 5G resource allocation, offering adaptive and scalable solutions across various operating conditions. However, its performance is highly dependent on the accuracy of predictions; insufficient representative training data may result in less than optimal allocation decisions. Furthermore, the presumption of flawless SIC in NOMA and a constant backhaul delay [19] could restrict practical implementation. In scenarios with high user densities, the exploration capacity of BSO may result in convergence to local optima, as indicated in

[31]. This observation implies that integrating reinforcement learning or diversity-enhancing metaheuristics could enhance robustness further. The adaptability, efficiency, and scalability of the DL–BSO framework make it a strong contender for future 6G systems that incorporate URLLC and ISAC capabilities. The training process for the LSTM module took approximately 2.3 minutes per epoch on a standard GPU. After training, the inference time was reduced to around 3 ms per decision, making it suitable for real-time MEC deployment. The findings were averaged over 20 iterations, accompanied by 95% confidence intervals; t-tests validated that the improvements were statistically significant ($p<0.05$) across various network sizes. The system is capable of deployment in telecom edge clouds and smart city slices, facilitating industrial IoT and AR/VR applications in accordance with URLLC requirements.

4. CONCLUSION

This study used DL and BSO to create a hybrid framework for dynamic and balanced computing resource allocation in MEC-enabled 5G networks. Predictive modelling and bio-inspired optimization were used to minimize latency, energy consumption, and operational expenses in complex wireless situations. The main innovation is the strong integration of LSTM-based traffic and channel prediction with multi-objective BSO optimization for proactive and adaptive allocation decisions. Unlike standard heuristic methods, the proposed DL–BSO framework uses predictive insights to begin and drive the optimization process, improving convergence speed and solution quality in dynamic NOMA-enabled MEC settings. Simulations under realistic 5G settings show that the DL–BSO framework outperforms heuristic and independent predictive approaches. Compared to baseline solutions, the strategy improved energy, delay, and cost by 54%. The results show that the framework reliably lowered energy usage at high offloading probability, maintained reduced latency with enough transmission power, and performed well in heavy-traffic scenarios with 100 active users. DL predictions, which depend on training data accessibility and quality, are essential to the system. Perfect SIC in NOMA and constant backhaul delay may not be maintained in real-world applications, diminishing benefits. The BSO algorithm may enter local optima at high user densities, restricting optimization. Future study will examine realistic SIC modelling and variable backhaul delays, add reinforcement learning into continuous online adaptation optimization, and widen the framework for 6G applications like ISAC and URLLC to improve robustness and scalability. Federated learning offers privacy-protected distributed model training. BSO with diversity-preserving metaheuristics can handle large-scale local optima. Focusing on predictive intelligence and adaptive optimization, the DL–BSO paradigm for intelligent resource allocation in next-generation wireless networks is practical and scalable. Constraints involve reliance on the quality of training data, the presumption of an optimal SIC, and challenges related to scalability under extreme loads. Future efforts will integrate reinforcement learning for ongoing adaptation, federated learning for privacy-conscious training, and validation through real-world telecom-grade testbeds.

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C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
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Va	:	**Va**lidation	O	:	Writing - **O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review & **E**diting			

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest regarding the publication of this paper.

DATA AVAILABILITY

No data was used for the research described in the article.

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