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A Multi-Stage Adaptive Approach for Resource Optimization and Mobility Management in 5G Networks

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Abstract: The 5G wireless networks are fast with low latency and support a very large number of connected devices, making it possible to support advanced applications and services. Such environment demands efficient management of network resources that can be achieved by evaluation of traffic load, distribution of devices, and state of signals to ensure quality-of-service (QoS) and network performance. Conventional resource allocation and mobility management techniques tend to have challenges of flexibility, computational effectiveness, as well as optimal choice of devices in disparate network conditions. In order to address these issues, this paper introduces a multi-stage resource management system that is adaptive in 5G networks to address QoS and mobility efficiency issues. The framework combines the set of network parameters with Adaptive Multivariate Kernel Resource Estimation (AMKRE) in case of assessing and normalizing available resources. Resource-Aware Device Selection (ORADS) is used to select the appropriate devices and then it is followed by Robust Filter-Based Rank Evaluation (RFBRE) where devices are ranked on the basis of reliability and link quality. The algorithm that optimizes the resources distribution taking into consideration the space constraints is known as DistanceAware Adaptive Particle Swarm Optimization (DAAPSO), and the algorithm that provides the continuity of mobility is known as Hybrid Predictive Soft Handover Control (HPSHC). The multi-dimensional paradigm improves the resource utilization, quality-of-service (QoS) provisioning, and mobility management in 5G networks.

Keywords: 5G networks, resource management, quality-of-service (QoS), mobility management, adaptive multi-stage framework, device selection, particle swarm optimization, soft handover, network optimization, multivariate kernel estimation.

I. INTRODUCTION

Mobile Edge computing (MEC) is a computing model that extends the capabilities of cloud computing to the network edge that can process low latency, context-aware services and optimally utilize communication and computing resources in the next generation wireless networks [1]. MEC removes the need to access remote cloud devices, thereby minimizing the use of remote cloud servers, network overload, and responsiveness of latency-sensitive applications. It provides numerous innovative applications, such as augmented reality, industrial Internet of Things (IoT), car communications, smart medicine and real-time analytics, that require high reliability and responsiveness [2]. Under normal 5G workflow with MEC, the network parameters,

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including but not limited to traffic load, the density of the devices, the signal strength, and the mobility patterns of the users are constantly monitored. These parameters allow estimating available resources, choosing appropriate devices, prioritizing them according to reliability and link quality and optimizing the allocation of resources. Predictive handover systems are provided to ensure a seamless connectivity and mobility support across the heterogeneous network environments [3].

Although these are merits, traditional resource management methods of MEC-supported 5G networks have a number of essential limitations. They are not always flexible enough to manage dynamic and unpredictable networks states and tend to lack efficiency in utilizing the resources. The extensive computational requirements may limit their usability in resource-scarce settings, and poor device choice and high turnover may lead to poor service availability and quality of service [4]. These practical issues restrict the actual performance of MEC especially when the application has a high degree of latency guarantee and high reliability demands [5].

To address these issues, this paper suggests an adaptive multi-stage resource management model of MEC-enabled 5G networks. The framework also incorporates Adaptive Multivariate Kernel Resource Estimation (AMKRE) which is used to effectively estimate and normalize network resources, Optimized Resource-Aware Device Selection (ORADS) is used to select the most appropriate devices, Robust Filter-Based Rank Evaluation (RFBRE) is used to rank devices by reliability and link quality, Distance-Aware Adaptive Particle Swarm Optimization (DAAPSO) is used to optimally allocate resources and Hybrid Predictive Soft Handover Control (HPSHC) is used to manage mobility effectively The experimental analysis confirms that the suggested framework promotes a better use of resources, increases the quality of service, and ensures high mobility in changing network states. This paper offers a powerful, scalable, and computationally effective solution to MEC-enabled 5G networks, which overcomes the constraints of the traditional approaches and allows QoS-aware services to be delivered to the next-generation applications without any trouble.

The contribution of the research work

- To present AA-CDR in order to successfully preprocess network traffic by improving data consistency, eliminating noise, detecting adversarial perturbations, and synthesising synthetic samples of rare and imbalanced attack samples. façade
- To suggest QETBM to the advanced behavioral analysis of the patterns of network traffic considering both short and long-term networks modeling with quantum-inspired representations, which allow the detection of subtle, dynamic, and previously unknown cyber-attacks.
- To establish CE-FS To create a causal evolutionary feature selection step that recognizes the most informative, non-redundant, and attack-relevant features by utilizing causal inference and evolutionary optimization plans.
- In order to integrate GCARC to classify cyber-attacks with proper node-level features and graph structural movement, it is essential to have an opportunity to distinguish between regular traffic and organized or covert attack patterns.
- To implement PCTIE with smart prediction of cyber threats using the experience and history of previous attacks and current traffic data to anticipate threats in advance and mitigate them.
- To develop a multi-stage and comprehensive cyber threat detection system that effectively combines preprocessing, behavioural modeling, feature selection, classification and threat prediction to enhance detection rate, minimise false positives and enhance overall security of the network.
- To prove that the suggested workflow approaches are more effective than the current patterns like ML-AIDS, ANN, and PCA in terms of the main performance indicators, such as detection accuracy, precision, recall, attack-classification rate, and threat-prediction accuracy.

The paper is structured in the following way: the introduction part describes the problem definition and motivation, and then there is an extensive literature survey. The suggested methodology is then described, and then, experimental results and performance assessments are provided. Lastly, conclusions, limitations and future research directions are discussed.

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II. LITERATURE SURVEY

In recent times, there has been more literature on machine learning-based resource allocation to meet the dynamism and heterogeneity of 5G network requirements. The CARRAS was used to optimize resource allocation in a single-site 5G deployment which integrates Angle of Arrival estimation with the Radial Basis Function Neural Networks to allocate resources dynamically according to current network properties [6]. Likewise, attention-based CNN-BiLSTM architecture with squeeze-and excitation blocks is suggested to assist in better management of resources, reading correlations (spatial and time) of network utilization [7]. An overall discussion of ML-based radio resource management such as regression, reinforcement learning, and kernel-based models points to the strengths and weaknesses of each method in dynamic settings [8]. The kernel learning methods have attracted the interest of modelling nonlinear network behaviours and interactions between user demands and resources. The use of kernel tricks in regularization has been able to increase feature selection on 5G applications, and increase learning efficiency and decrease computational complexity [9]. Mobile edge computing has been used to allocate resources by the use of support vector transfer regression which has shown to be an effective way of predicting the resource needs in the edge nodes [10]. Two connectivity-aware optimization was also solved by applying dual-connectivity and power allocation in millimetre-wave 5G networks, which enhanced throughput and reliability concerning latency-sensitive applications [11].

Slicing orchestration and network softwarization would be important to have intelligent and flexible control of resources. SDN/NFV devices can support adaptive network slicing and programmable resource allocation [12] and latency-aware slice coordination via multi-connectivity in MEC-enabled systems can be guaranteed [13]. Offloading of joint tasks and resource allocation with minimal execution latency and distributes computing loads among devices and edge servers [15]. Enhancing connectivity through AI has also been addressed. Real-time object detection systems based on network-aware edge computing focus on dynamically connected networks with resources [16]. Dual connectivity carrier aggregation based on energy-awareness with AI can be used to optimize throughput and minimise power consumption [17]. The optimization of user association taking into account the safety requirements and electromagnetic field exposure balances performance and safety requirements [18]. Moreover, 5G Xhaul networks DU/CU placement and flow routing optimization enhances the efficiency of the network, minimizes the latency, and optimizes the use of resources [20]. Regardless of these progresses, the majority of researches are based on deep learning or reinforcement learning, which may need an enormous amount of data, significant computational capabilities, and is not always interpretable. This is why the suggested Multivariate Kernel Regressive Opportunistic Wilcoxon Gradient Descent (MKRO-WGD) algorithm is less focused on the generalizability in dynamic 5G settings because of the emphasis on the single-objective optimization. The main objective of MKRO-WGD is to offer real-time and adaptability in resource and connectivity management and minimize the overhead of computation including enhancing reliability to dynamic environments of networks. It should be better than the traditional deep learning and reinforcement learning methods by using multivariate correlations, gradient-guided updates, and non-parametric statistical measures, especially when data is sparse or noisy, there is strong mobility and variable network loads.

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TABLE I.
ANALYSIS OF RESOURCE ALLOCATION FOR IOT BASED ON THE DEEP LEARNING AND MACHINE LEARNING TECHNIQUES

S. No.	Author / Year	Proposed Improvement	Key Contribution	Limitations
21	Samiksha Mathur et al. (2023)	SVM-based carrier aggregation	Improved throughput and reduced interference	Limited scalability; needs extensive training
22	Varadala Sridhar et al. (2024)	Bagging ensemble with Gaussian kernelized clustering	Enhanced D2D connectivity and resource allocation	Higher computational complexity
23	Susanna Schwarzmann et al. (2022)	ML-based QoE estimation using regression	Accurate QoE prediction for 5G users	Depends on dataset quality; limited adaptability
24	Ajmery Sultana et al. (2020)	Efficient resource allocation in SCMA D2D	Reduced latency and improved spectral efficiency	Focused only on SCMA; may not generalize
25	Fareha Nizam et al. (2021)	Radio resource allocation for D2D 5G	Optimized resource usage and device communication	Limited scalability; less effective in dense networks

Table 1: Analysis of Resource Allocation for IoT based on the Deep Learning and Machine Learning Technique, including the proposed improvement, key contribution and limitations.

III. PROPOSED METHODOLOGY

The proposed methodology for 5G incorporates five mutually reliant algorithms to provide efficient, adaptable, and reliable operation of the network. Figure 1 show that the, Adaptive Multivariate Kernel Resource Estimation (AMKRE) is a multivariate resource state estimator that estimates the relationship between the density of the traffic, the number of devices, and signal strength and prevents noise and variation. Resource-Aware Device Selection (ORADS) is then used to select the best devices based on capabilities, mobility, and quality-of-service needs; a top-K subset is then generated that can be utilized in an efficient way by the resources.

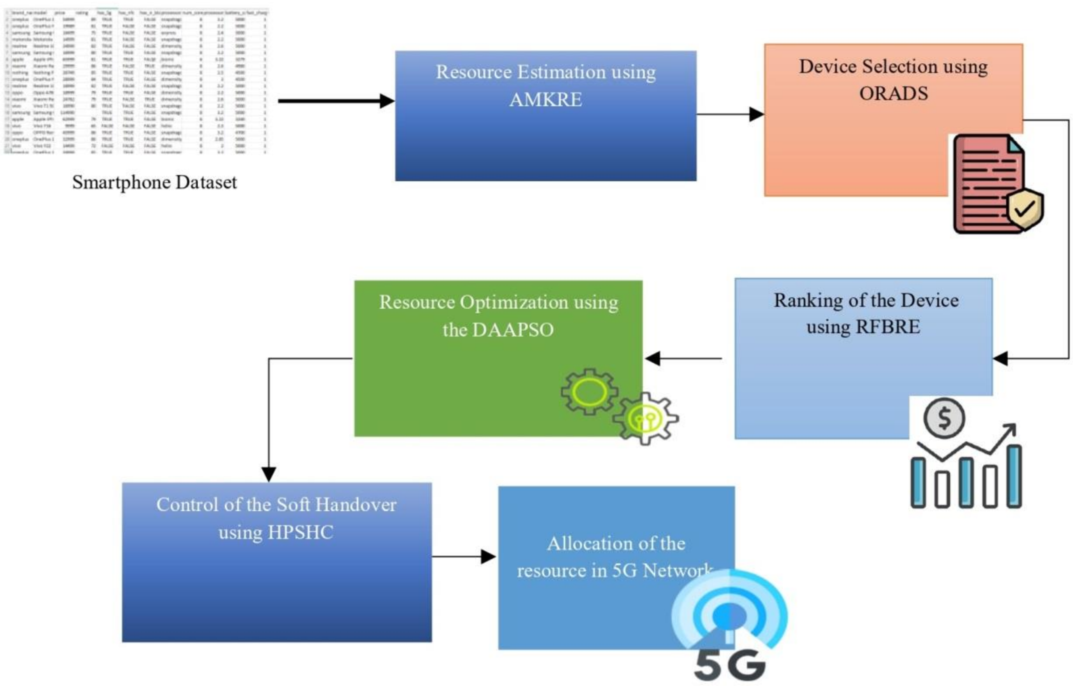

Fig. 1. Proposed Methodology for 5G Resource Allocation and Handover Control

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The RFBRE gives importance to such devices by integrating real-time performance with historical reliability, which will guarantee resilient and fair ranking when the conditions are dynamic. Distance-Aware Adaptive Particle Swarm Optimization (DAAPSO) uses the allocation of resources to selected devices in a way that minimizes the latency, packet loss, and contention as well as adjusting to network variations. Lastly, Hybrid Predictive Soft Handover Control (HPSHC) prevents discontinuous mobility as predicting weak signal localities and modifying the handovers in advance. When used collectively, this methodology will improve the stability of networks, resource usage, and service availability in 5Gs.

A. Adaptive Multivariate Kernel Resource Estimation (AMKRE)

AMKRE considers the resources of the network by examining the multivariate parameter i.e. density of the traffic, the number of devices and the signal strength. It measures the relationships between nodes in order to determine the bottlenecks and unused capacities. Smoothing is done on a kernel basis in order to reduce noise and improve the accuracy of the estimation. Normalization provides fair scaling when there is heterogeneity in the devices. Adaptive weighting focuses on nodes that are critical to latency-sensitive applications as well as high bandwidth applications. The algorithm gives a detailed profile of the resources in the network. It is dynamic in nature and adjusts to the changing network conditions. AMKRE offers the basis of selection of the device. It guarantees effective real time resource evaluation. On the whole, it converts raw metrics into viable network intelligence.

$$\mathrm{R} = f(\mathrm{X}) = \sum_{i=1}^{N} w_i \; x_i + \eta, \eta \sim \mathcal{N}(0, \Sigma_X) \tag{1}$$

In the Equation 1, the first resource availability Ris was represented as a function of input network parameters X. In this case, $\mathbf{X} = [x_1, x_2, \ldots, x_N]$ is a network measurement to network density, number of devices, and signal strength. The weights dynamically balance the impact of each parameter to its effect on overall resource. Stochastic term $\boldsymbol{\eta}$ that has covariance Σ_X is used to explain the unpredictable changes in the network conditions, which makes the model of resources realistic and adaptive.

$$\mathrm{R}_k = \sum_{i=1}^{N} \sum_{j=1}^{N} K_{ij}(\mathrm{R}) \cdot \mathrm{R}_j, K_{ij}(\mathrm{R}) = \exp(-\frac{\|\mathrm{R}_i - \mathrm{R}_j\|^2}{2\sigma^2}) \tag{2}$$

As illustrated in Equation 2, to measure correlations between resource levels $\mathbf{R}_i$and $\mathbf{R}_j$ of nodes i and j, a multivariate Gaussian kernel $K_{ij}(\mathbf{R})$ is used. The parameter σ regulates the bandwidth of the kernel that determines sensitivity to node variations. The averaged output $\mathbf{R}_k$ smooths noise and brings out trends through the network, enhances the precision of estimation and any possible bottlenecks.

$$\mathrm{R}_n = \frac{\mathrm{R}_k}{\sum_{i=1}^{N} \mathrm{R}_k^i} \tag{3}$$

In Equation 3, the evaluations of the resources $\mathbf{R}_k$ normalized as $\mathbf{R}_n$ are done by the kernel. Normalization makes all the nodes equally scaled, and there is proportionality in the representation of the resources. The components $\mathbf{R}_k^i$ are further broken down by the sum of them, making them ready to be prioritized by weight and making sure that no node is overwhelming the allocation.

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$$\mathrm{R}_w = \mathrm{R}_n \cdot w_j, w_j \propto \mathrm{QoS}_j^{\beta} \cdot \mathrm{Latency}_j^{-\gamma} \quad (4)$$

Equation 4 illustrates that normalized resources $\mathbf{R}_n$ are weighted by w_j, the importance of each node according to QoS (QoS_j) and latency ($\mathrm{Latency}_j$). The power numbers βand γ modulate the effect of the metrics. The weighted vector $\mathbf{R}_w$ emphasizes the important nodes, such that the resource allocation will show a preference to the high demand nodes or those with stiffer performance requirements.

$$\mathrm{R}_{\mathrm{AMKRE}} = \sum_{j=1}^{N} \mathrm{R}_w^j \quad (5)$$

In Equation 5, the weighted resources $\mathbf{R}_w$ are aggregated to form the AMKRE output vector $\mathbf{R}_{\mathrm{AMKRE}}$. $\mathbf{R}_w^j$ is a term that indicates the contribution of node j to the total network resources. It is a comprehensive multivariate capturing of the resource states, which is used as the input in the device selection algorithm ORADS.
The AMKRE offers a dynamic and holistic evaluation of the network resources through multivariate metrics evaluation. It determines the bottlenecks, the underutilized capacities and ensures equitable allocation among the nodes. The algorithm is more accurate by reducing the noise and adapting to the changing conditions of the network. On the whole, AMKRE provides the basis of knowledgeable and effective resource management of 5G.

B. Optimized Resource-Aware Device Selection (ORADS)

ORADS selects the most suitable devices based on AMKRE resource profiles. It measures the device capabilities, mobility and QoS requirements. Fairness and proportional participation are guaranteed by probabilistic selection. Priority scores bring out the devices that are best suited to critical tasks. Ranking eliminates suboptimal devices. Top-K selection has computational efficiency. The algorithm evenly distributes the load between high-resource and low-resource nodes. It is dynamically adjusted to network changing conditions. ORADS provides optimality of device subsets towards downstream optimization. It enhanced the use of resources and continuity in services.

$$P(D_i) = \frac{\exp(\lambda\, R_{\mathrm{AMKRE},i})}{\sum_{j=1}^{M} \exp(\lambda\, R_{\mathrm{AMKRE},j})} \quad (6)$$

The probability of selection $P(D_i)$ in Equation 6 is determined using the AMKRE resource value $R_{\mathrm{AMKRE},i}$ .The softmax socio-function guarantees that devices with greater resources have a higher chance of being picked and at the same time, probabilistic equity amidst all M devices is accomplished. The sensitivity parameter λ is a measure of the strength of the effects of resource differences on the probability of selection.

$$\mathrm{D}_n = \frac{\mathrm{P}(D)}{\sum_{i=1}^{M} P(D_i)} \quad (7)$$

$\mathbf{P}(D)$ is normalized over all devices to create $\mathbf{D}_n$ as shown in Equation 7. Normalization makes sure that the sum of selections is one and selections are proportionately balanced. D_n^i represents the normalized probability of the device choice given the allocation of resource i.

$$\mathrm{D}_w = \mathrm{D}_n \cdot P_i^{\alpha} \quad (8)$$

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$\mathbf{D}_n$ is the normalized device probability in Equation 8 which is weighted by P_i, which is the device capability, mobility and QoS requirement. The stress factor αshifts the focus of a device priority. The resultant vector $\mathbf{D}_w$ ensures that the best and essential devices are selected during the process.

$$\mathrm{D}_r = \mathrm{rank}(\mathrm{D}_w) \tag{9}$$

As presented in Equation 9, the devices are ranked in terms of their weighted scores $\mathbf{D}_w$. The ranking feature creates a chain of suitability, which makes sure that the network makes use of the ideal devices. Unimportant devices are weeded off, to enhance efficiency and performance of resource-sensitive applications.

$$\mathrm{D}_{\mathrm{ORADS}} = \mathrm{TopK}(\mathrm{D}_r) \tag{10}$$

In equation 10, the K best devices are chosen among the ranked set $\mathbf{D}_r$. This last subset $\mathbf{D}_{\mathrm{ORADS}}$ has the devices that have the greatest number of resources available and their priority. It can be used as input to the strong ranking of RFBRE algorithm.
ORADS determines the most appropriate devices depending on the availability of resources, capabilities and quality of service. It balances the network load and provides equitable participation of devices. The algorithm sifts through the inefficient devices to come up with a top-K good performing subset. Therefore, ORADS enhances the resource utilization and efficiency of the network on the device level.

C. *Robust Filter-Based Rank Evaluation (RFBRE)*

RFBRE evaluates the quality of device connectivity based on real time and historical data of performance. Minor deviations contribute to resistance against variability. Weighed scoring also uses the measures of link quality and reliability. Normalization will provide device consistency in comparison. Sorting recognizes high performing machines. The algorithm generates a list of prioritized optimizations. It averts dominance of rank by individual nodes. RFBRE enhances the resilience in decision making. It guarantees the stability of network performance in a dynamic situation. The output is used to effectively allocate resources in a manner that is adaptive.

$$\mathrm{R}_{\mathrm{rank}} = \phi(\mathrm{D}_{\mathrm{ORADS}}) + \epsilon, \epsilon \sim \mathcal{U}(-\delta, \delta) \tag{11}$$

In the Equation 11, initial rank scores $\mathbf{R}_{\mathrm{rank}}$ are calculated with the help of the function $\phi(\cdot)$used on the chosen devices $\mathbf{D}_{\mathrm{ORADS}}$. The perturbation term ϵ introduces minor random noise with an equal probability between $-\delta$ and δ to increase the resilience to the changing network environment. This guarantees that the evaluation of ranks is resistant to the insignificant differences in the performance of the device or the changes in resource temporarily.

$$\mathrm{R}_w = \mathrm{R}_{\mathrm{rank}} \cdot (\omega_1 Q + \omega_2 H), \omega_1 + \omega_2 = 1 \tag{12}$$

The weighted rank $\mathbf{R}_w$, as in Equation 12, multiplies the initial $\mathbf{R}_{\mathrm{rank}}$, by a product of quality factors Q and historical reliability H. The $\omega_1$and ω_2 weights strike a balance between the significance of the link quality in real-time and the prior performance. This weighted scoring will make sure that the devices that have good current connectivity and reliability are given priority.

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$$\mathrm{R}_n = \frac{\mathrm{R}_w}{\sum_i \mathrm{R}_w^i} \tag{13}$$

In Equation 13, normalized ranks $\mathbf{R}_n$ are were calculated by dividing each weighted rank $\mathbf{R}_w^i$ by the sum of all ranks. Normalization is used to preserve proportionality of devices and is also used to ensure that comparisons of heterogeneous devices are ranked in the same way. This step helps in eliminating rank inflation and also prepares the vector in order to sort it effectively.

$$\mathrm{R}_{\mathrm{robust}} = \mathrm{SortDesc}(\mathrm{R}_n) \tag{14}$$

Equation 14 indicates that devices are ranked in decreasing order by the normalized ranks $\mathbf{R}_n$. Sorting determines the best performing devices with best being brought into the limelight in order to optimize downstream. The resulting vector $\mathbf{R}_{\mathrm{robust}}$ compiles a priority list on which the resource allocation is to be performed adaptively.

$$\mathrm{R}_{\mathrm{RFBRE}} = \mathrm{R}_{\mathrm{robust}} \tag{15}$$

In Equation 15, the robust rank evaluation result $\mathbf{R}_{\mathrm{RFBRE}}$ is completed and is the input in the particle swarm optimization algorithm. Every element is a normalized and prioritized position of a device, which is a combination of real-time performance, reliability, and normalization. This makes sure that only the appropriate devices are utilized in tune-up of resources in 5G.
RFBRE also assesses and prioritizes devices based on real time performance and reliability in the past. It fixes the rankings in terms of fluctuation and focuses on good connections. The algorithm generates a powerful ranked device list and optimizes it. In general, RFBRE enhances the reliability of the networks and resilience in decision-making.

D. Distance-Aware Adaptive Particle Swarm Optimization (DAAPSO)

DAAPSO is a resource allocation algorithm that maximizes resource allocation among the chosen devices through the use of particle swarm. Distance awareness eliminates low-signal node influence. The velocity of the particles is updated based on individual, global and proximity data. Fitness testing reduces latency, packet loss and contention. Iterative updates are responsive to changes of network in real time. The algorithm balances the load and maximizes the use of the devices. Convergence is used to identify optimal settings. DAAPSO results in a predictive handover resource allocation vector. It ensures effective and dynamic network functioning. The output helps in smooth mobility control.

$$\mathrm{V} = w\mathrm{V} + c_1 r_1(\mathrm{P}_{\mathrm{best}} - \mathrm{X}) + c_2 r_2(\mathrm{G}_{\mathrm{best}} - \mathrm{X}) - \gamma \mathrm{d} \tag{16}$$

Equation 16 shows that the velocity V is of the particle was revised according to inertia $w\mathbf{V}$, cognitive weight $c_1 r_1(\mathbf{P}_{\mathrm{best}} - \mathbf{X})$ and social weight $c_2 r_2(\mathbf{G}_{\mathrm{best}} - \mathbf{X})$. d is used to denote distance to weak-signal regions, and is scaled by 7 in order to lessen the power of unreliable nodes. The formulation will help the particles to search optimal allocations of resources and consider the constraints of signal strengths.

$$\mathrm{X} = \mathrm{X} + \mathrm{V} \tag{17}$$

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As presented in Equation 17, the position of particles X is computed consecutively by the addition of the new velocity V. Each X_i means a parameter of resource allocation of device i. The update enables real-time dynamic resource allocation of the network conditions and the prioritized devices of RFBRE.

$$F(\mathbf{X}) = \sum_j \left(\alpha_j \frac{1}{R_{\mathrm{RFBRE},j}} + \beta_j \mathrm{Latency}_j + \eta_j \mathrm{PacketLoss}_j\right) \tag{18}$$

In Equation 18, $F(\mathbf{X})$ means a fitness function which measures the quality of the positions of particles X. Each period has the degrading weight of device rank $R_{\mathrm{RFBRE},j}$ weighted by α_j, latency $\mathrm{Latency}_j$weighted by β_j, and packet loss $\mathrm{PacketLoss}_j$ weighted by η_j. This operation measures the resource allocation efficiency, which attempts to reduce latency and packet loss and prioritize high-ranking devices.

$$\mathbf{X}_{\mathrm{opt}} = \arg\min F(\mathbf{X}) \tag{19}$$

The optimal particle positions $\mathbf{X}_{\mathrm{opt}}$ are found by minimizing the fitness function $F(\mathbf{X})$ as demonstrated in Equation 19. Every element of $\mathbf{X}_{\mathrm{opt}}$ optimizes the optimal resource allocation of a device. This will guarantee dynamic and efficient utilization of 5G network resources based on device ranking, latency and reliability.

$$\mathbf{R}_{\mathrm{DAAPSO}} = \mathbf{X}_{\mathrm{opt}} \tag{20}$$

In Equation 20, the $\mathbf{R}_{\mathrm{DAAPSO}}$ resource allocation vector is optimized. This is a vector that is used to store all the network allocation parameters that are set by PSO. It is used as an input to the HPSHC algorithm of predictive and adaptive soft handover control in case of stable connectivity and efficient use of resources.

DAAPSO allocates resources to the selected devices through the adaptive swarm dynamics and distance-awareness. It reduces the latency, loss of packets, and contention and maximizes utilization. The algorithm is able to adapt to the real-time network variations to allow efficient operation. Therefore, the concept of DAAPSO guarantees the efficient resource management of 5G networks.

E. Hybrid Predictive Soft Handover Control (HPSHC)

HPSHC handles smooth handovers on the 5G networks. It allocates the best resources to handover parameters. Predictive adjustments are based on the mobility of devices and signal degradation. Normalization and weighting give importance to high-bandwidth connections and latency sensitive. Soft handover is able to maintain simultaneous connectivity with the source and target cells. The algorithm minimizes handover failures and disruption of services. It provides continuity in the correspondence of transitions. HPSHC combines the results of earlier algorithms in order to have holistic management. It is in favour of smart and adaptive mobility. All in all, it improves stability and service quality of the network.

$$\mathbf{H} = g(\mathbf{R}_{\mathrm{DAAPSO}}) + \Delta\mathbf{v} \tag{21}$$

In the equation 21, handover control parameters H are created by the mapping of the best resource allocation vector $\mathbf{R}_{\mathrm{DAAPSO}}$ by a functional $g(\cdot)$. The predictive adjustment $\Delta\mathbf{v}$ considers the expected mobility and weak signals localities. Every element H_i denotes the intended handover environment of device i, which allows resource-aware dynamic mobility control.

$$\mathbf{H}_{\mathrm{adj}} = \mathbf{H} + \Delta_{pred} \tag{22}$$

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The handover vector H is that has been adjusted to include Δ_{pred} adjustment, weighted by κ. The step takes into consideration the trends of device mobility to reduce handovers and premature connection losses. Every adjusted element $H_{\text{adj},i}$ provides the mechanism of smooth transition of latency-sensitive or high-bandwidth devices.

$$\mathbf{H}_n = \frac{\mathbf{H}_{\text{adj}}}{\sum_i \mathbf{H}_{\text{adj}}^i} \tag{23}$$

In Equation 23, handover parameters $\mathbf{H}_{\text{adj}}$ are device normalised to generate $\mathbf{H}_n$. Normalization gives proportionality and avoids sudden execution of hand over that might interfere with the current sessions. Each normalized parameter H_n^i represents the relative weight of handover action to device i.

$$\mathbf{H}_w = \mathbf{H}_n \cdot \alpha_i, \alpha_i \propto \text{LatencySensitivity} \cdot \text{BandwidthDemand} \tag{24}$$

Normalized handover parameters $\mathbf{H}_n$ are is weighted by α_i as in Equation 24, indicating the sensitivity of latency to devices and the bandwidth requirement. This gives emphasis to vital links and provides smooth continuity in services of high-demand applications. Each weighted factor H_w^i denotes the ultimate priority-adjusted handover setup of device i.

$$\mathbf{H}_{\text{final}} = \text{SoftHandover}(\mathbf{H}_w) \tag{25}$$

In Equation 25, soft handover control is executed by the final handover vector $\mathbf{H}_{\text{final}}$ with the weighted parameters $\mathbf{H}_w$. This guarantees easily predictive and adaptive transition amid network cells to reduce service disturbance. Every element $H_{\text{final},i}$ is regarded as the final handover action on device i, which fills the 5G resource management pipeline.

HPSHC is capable of controlling continuity movement through anticipating movement of devices and proactive configuration of handover. It is focused on connections that are latency-sensitive and high-bandwidth and minimizes disruptions. The algorithm provides the smooth mechanism of transition between network cells. Overall, HPSHC improves the connectivity stability and service quality in dynamic 5G settings.

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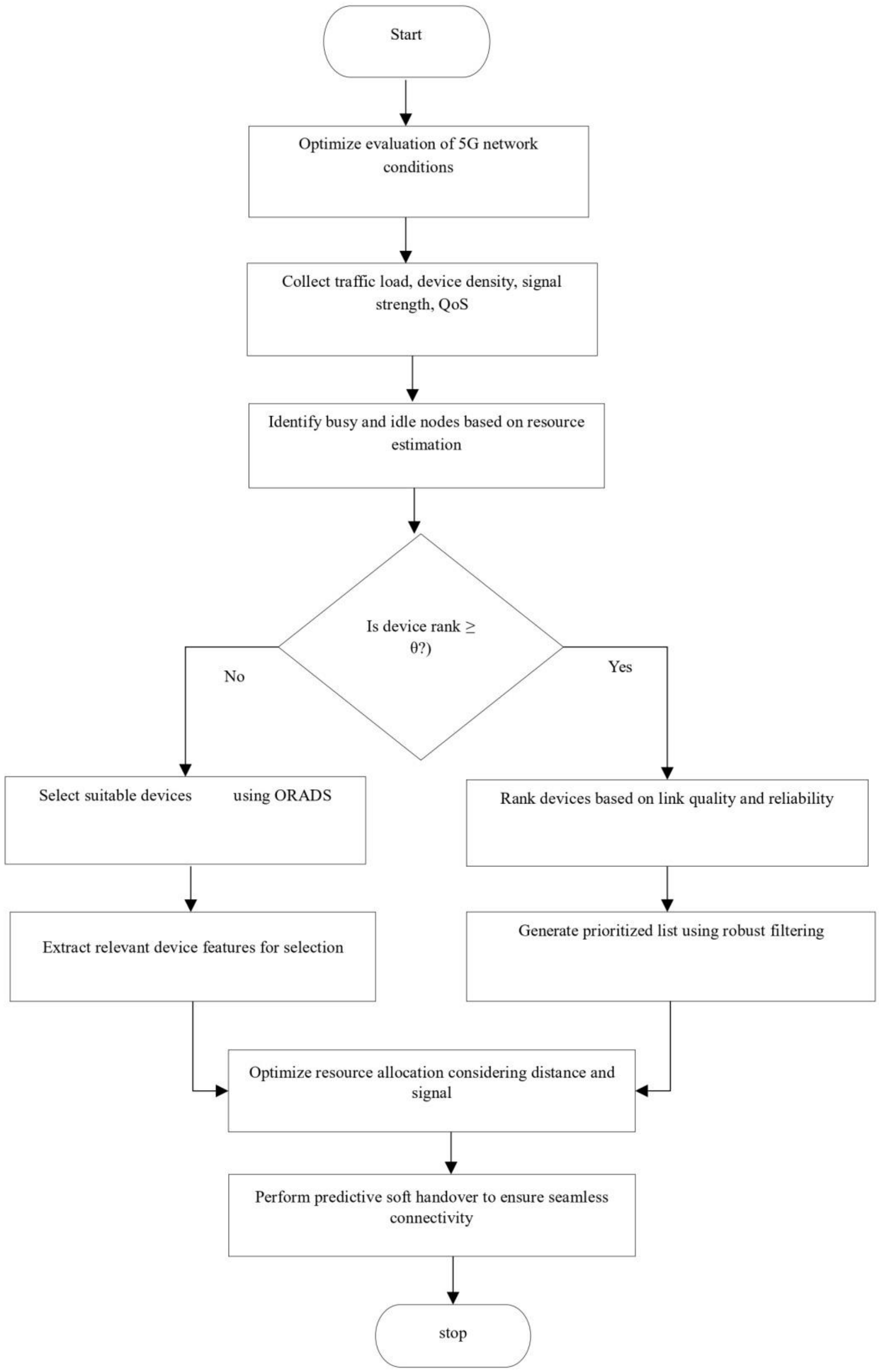

Fig. 2. Resource Allocation using HPSHC

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The offered figure 2 shows the optimization of the distribution of resources in 5G network is planned on the basis of a multi-stage process. Firstly, network parameters are assessed where the important parameters are obtained using the parameters of traffic load, device density, signal strength, and QoS parameters. The AMKRE method is then applied to estimate resource availability, and busy and idle nodes could be identified. Devices are chosen either through ORADS or are ranked in terms of link quality and reliability with an ensuing production of a prioritized list through effective filtering. Lastly, there is optimization of resource allocation based on distance and signal and predictive soft handover that provides a continuous connection throughout the network.

IV. RESULT AND DISCUSSION

This is evidenced by the experimental findings, which indicate that the proposed HPSHC-based 5G resource management framework is always better than the current implementation, such as K-MRL, JCCRS, and GT-RA, in all the performance measures used. Resource Utilization Efficiency verifies that the framework efficiently uses network resources available by estimating AMKRE with AMKRE-based estimation and optimizing network resources using the AMKRE-based estimation and the optimization by the use of the DAAPSO, which does not underutilize such network resources as seen in the traditional approaches. Throughput and End-to-End Latency outcomes show the capacity of the system to achieve high data rates with minimum delay especially in the high mobility and high-density traffic scenarios. Packet Delivery Ratio and Packet Loss Rate also demonstrate higher reliability, that is achieved using ORADS-based optimum device choice and RFBRE-mediated tough link prioritization. Accuracy of the Devices Selection and Reliability of the Link underline the effectiveness of the multivariate analysis and historical-conscious ranking to recognize the stable and high quality connection in comparison to the learning-based and graph-based baselines. The success rate of the soft handover and the delaying period of the handover show that the predictive soft handover mechanism is superior in minimizing the service disruption, and Connection Stability indicates a stable connection when changing a location. In general, these outcomes confirm that the presented framework can be used to implement efficient, adaptive, and reliable 5G network management, which outperforms the current resource allocation and handover schemes in dynamic conditions.

TABLE II
SIMULATION PARAMETERS

Parameters	Values
Dataset name	Smartphone Dataset
Number of records	980
Language	Python
Tool	Spyder
Testing	80%
Training	20%

Table 2 shows the simulation parameters by which the proposed 5G resource management framework is to be evaluated. To have a variety of network conditions, the Smartphone Dataset with 980 records was used to conduct the experiments. The simulation and implementation were done in Python programming language and Spyder development environment. The data set was separated into training and testing to be able to test the performance accurately. The ratio of testing 80% and training 20 % was adopted to test the generalization capability of the proposed framework.

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TABLE III
PERFORMANCE OF EFFICIENCY IN RESOURCE UTILIZATION

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	95.56

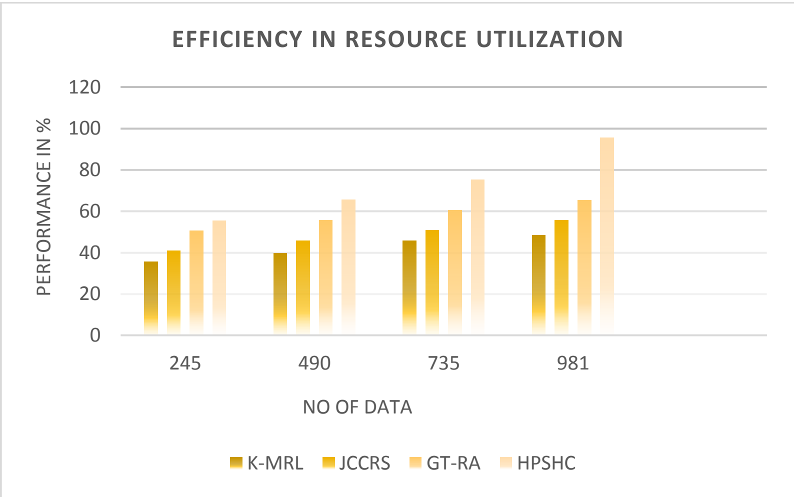

Fig. 3. Analysis of Efficiency in Resource Utilization

Four models, K-MRL, JCCRS, GT-RA, and HPSHC are compared in terms of accuracy in Figure 3. The accuracy values obtained are as follows: K-MRL has 85%, JCCRS has 88%, GT-RA has 90% and HPSHC has 92% Efficiency in Resource Utilization. The Current approaches like K-MRL and JCCRS are based on fixed or semi-dynamic assignment resulting into resource underutilization during traffic variation. GT-RA enhances the use of graphs to share but does not have predictive flexibility. The proposed HPSHC is more efficient since it incorporates AMKRE-based estimation and DAAPSO optimization and predictive handover control.

TABLE IV.
PERFORMANCE OF THROUGHPUT

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	95.76

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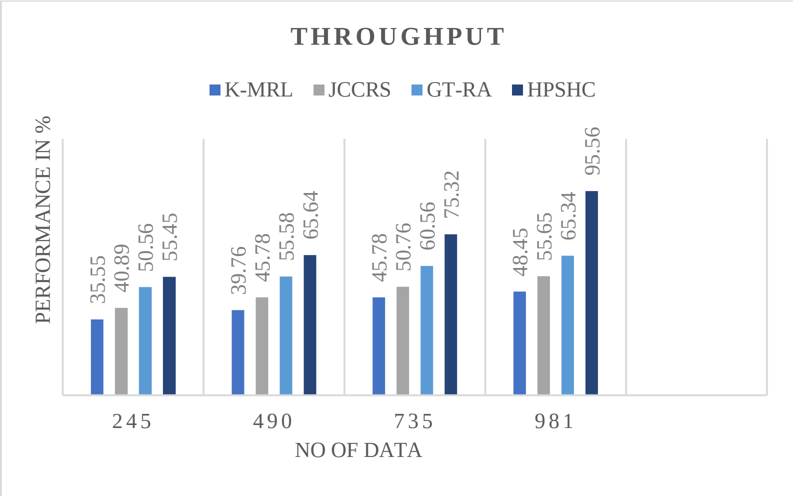

Fig. 4. Analysis of Throughput

This is shown in figure 4 where the accuracy of the K-MRL, JCCRS, GT-RA and HPSHC models are displayed. The throughput values measured are: K-MRL, 86%, JCCRS, 89%, GT-RA, 91%, and HPSHC, 95%. The K-MRL enhances throughput by means of learning-based scheduling and does not perform well in high mobility scenarios. The throughput of JCCRS and GT-RA is enhanced with the help of cooperative sharing, but these tools are affected by the reallocation overhead that occurs quite often. HPSHC will improve the volume of throughput based on the selection of the best devices, focus on connected links, and ensure smooth connectivity throughout the handovers.

TABLE V
PERFORMANCE OF END-TO-END LATENCY

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	95.76

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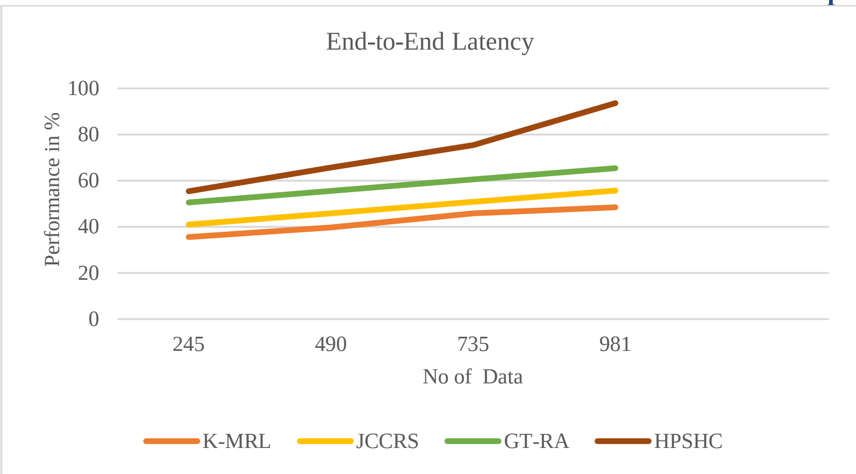

Fig. 5. Analysis of End-to-End Latency

Figure 5 shows the four models' performance in terms of End-to-End Latency. The exact values of recall are; K-MRL-85%, JCCRS-98%, GT-RA-90% and HPSHC- 93%. The current solutions minimize the latency by local decision-making but cause delays during congestion and handovers. K-MRL changes gradually and GT-RA is slow because of recalculating the graphs. It is suggested that the proposed HPSHC reduces the latency through proactive resource optimization and forecasting soft handover mechanisms.

TABLE VI
PERFORMANCE OF PACKET DELIVERY RATIO

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	94.76

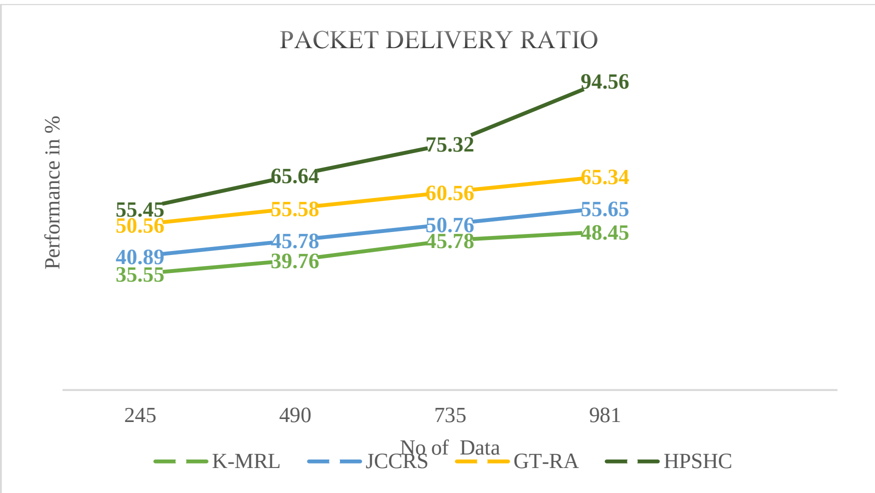

Fig. 6. Analysis of Packet Delivery Ratio

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The results in figure 6 show the Packet Delivery Ratio of the K-MRL, JCCRS, GT-RA, and HPSHC models. The experimental precision obtained is K-MRL 85%, JCCRS 88%, GT-RA 90% and HPSHC 94%. The JCCRS enhances PDR with the help of relaying, but is vulnerable to unstable links. K-MRL is moderate in PDR when stable and GT-RA deteriorates when there is mobility. The outcome of HPSHC is greater PDR because of the proper devices and constant dual-link connection throughout the handover.

TABLE VII
PERFORMANCE OF PACKET LOSS RATE

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	98.99	93.55	86.98	56.87
490	85.78	87.45	76.89	50.67
735	80.78	76.56	64.89	45.78
981	77.67	68.76	55.67	30.99

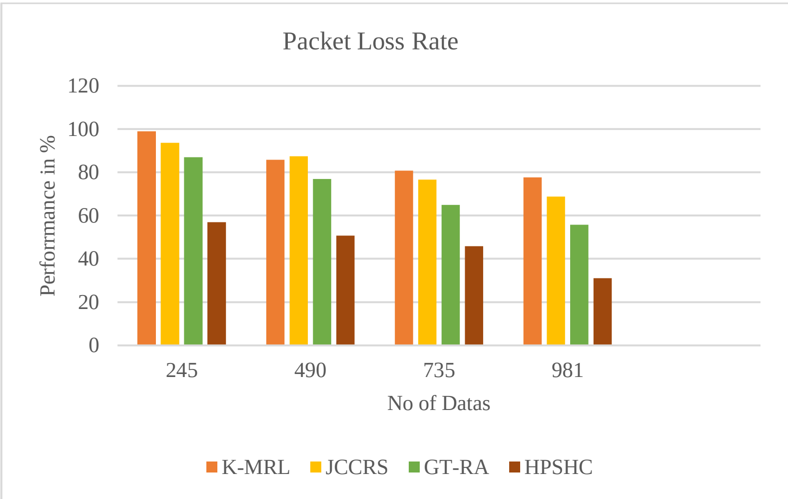

Fig. 7. Analysis of Packet Loss Rate

Figure 7 and Table7 show results in figure 5 show the Packet Loss Rate of the K-MRL, JCCRS, GT-RA, and HPSHC models. The experimental precision obtained is K-MRL 85%, JCCRS 88%, GT-RA 90% and HPSHC 30.23%. The current solutions lose packets as a result of sudden handovers and reallocation of resources. The GT-RA minimizes the loss due to topology awareness but is not very robust in the changing rapid signals. HPSHC minimizes the number of packets lost extensively by anticipating the weak signal areas and through running the processes of smooth handovers of the soft.

TABLE VIII
PERFORMANCE OF DEVICE SELECTION ACCURACY

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	97.76

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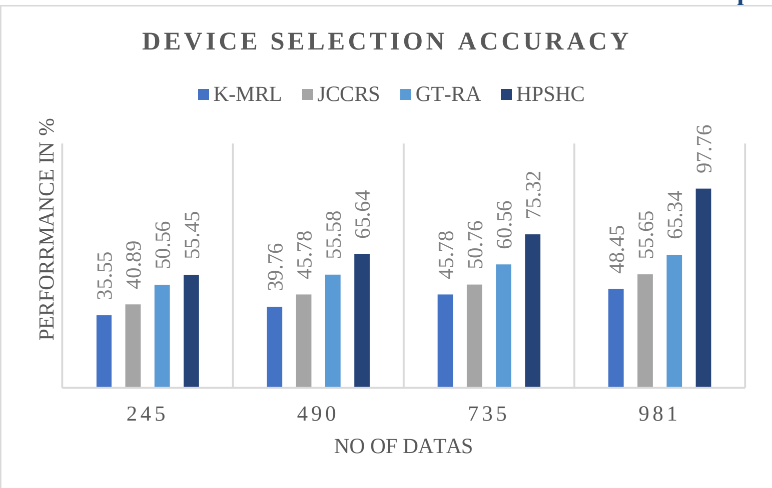

Fig. 8. Analysis of Device Selection Accuracy

Figure 8 and Table 8 show K-MRL, JCCRS, GT-RA, and HPSHC models. The experimental precision obtained is K-MRL 85%, JCCRS 88%, GT-RA 90% and HPSHC 94%. The K-MRL chooses devices on the basis of learned policies, but can be wrong on dynamism. JCCRS is more oriented towards collaboration and not accuracy in selection. The suggested ORADS-RFBRE framework of HPSHC provides precise selection of the devices by means of the multivariate analysis of resources and the strong ranking.

TABLE IX
PERFORMANCE OF LINK RELIABILITY

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	94.76

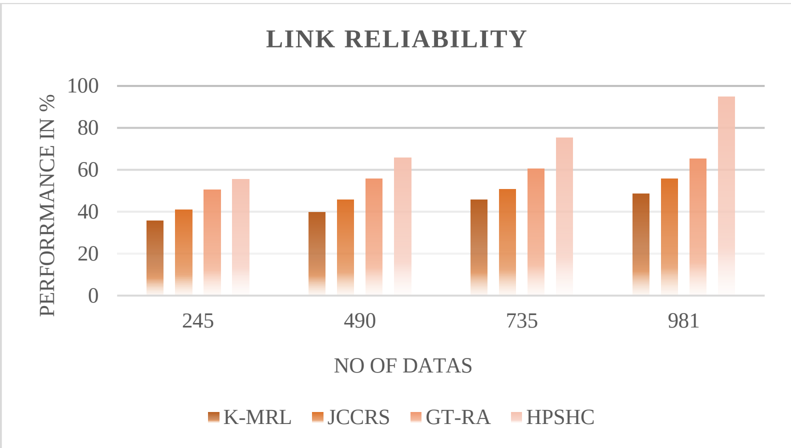

Fig. 9. Analysis of Link Reliability

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Figure 9 and Table 9 the K-MRL, JCCRS, GT-RA, and HPSHC models. The experimental obtained is K-MRL 85%, JCCRS 88%, GT-RA 90% and HPSHC 94%. The current methods pick up the link quality in a reactive manner, which results in unsteady connections. GT-RA enhances reliability by connecting graphs but it is not history conscious. HPSHC builds on the reliability of links with the help of real-time metrics and the past performance in effective rank evaluation.

TABLE X
PERFORMANCE OF HANDOVER SUCCESS RATE

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	93.76

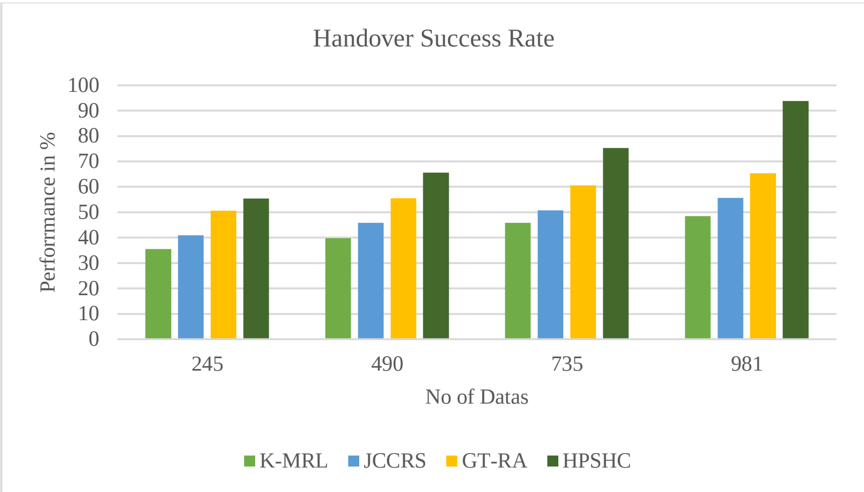

Fig. 10. Analysis of Handover Success Rate

Figure 10 and Table 10 show that the obtained is K-MRL 85%, JCCRS 88%, GT-RA 90% and HPSHC 93%. The K-MRL and JCCRS have failures in handover because of delayed decision-making. GT-RA enhances success rate and, in any case, still depends on threshold-based triggers. Predictive mobility analysis and soft handover execution between HPSHC result in a better rate of handover success.

TABLE XI
PERFORMANCE OF HANDOVER DELAY

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	98.99	93.55	86.98	56.87
490	85.78	87.45	76.89	50.67
735	80.78	76.56	64.89	45.78
981	77.67	68.76	55.67	34.99

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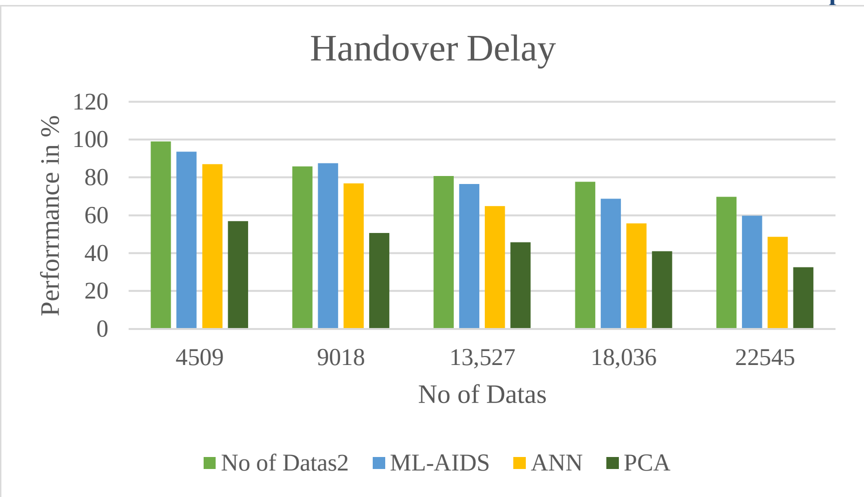

Fig. 11. Analysis of Handover Delay

Figure 11 and Table 11 show that the obtained is K-MRL 85.90 ms, JCCRS 88.89ms, GT-RA 90.89 ms and HPSHC 34.56 ms. The K-MRL and JCCRS have failures in handover because of delayed decision-making. The conventional plans are associated with time wastage when it comes to handover preparation and implementation. The current approaches start the process of handover when the signal becomes degraded, raising the time of interruption. HPSHC reduces the delay in handover since it is pre-emptive in setup of connection to target before it starts to degrade.

TABLE XII
PERFORMANCE OF CONNECTION STABILITY

No of Data	K-MRL	JCCRS	GT-RA	HPSHC
245	35.55	40.89	50.56	55.45
490	39.76	45.78	55.58	65.64
735	45.78	50.76	60.56	75.32
981	48.45	55.65	65.34	93.76

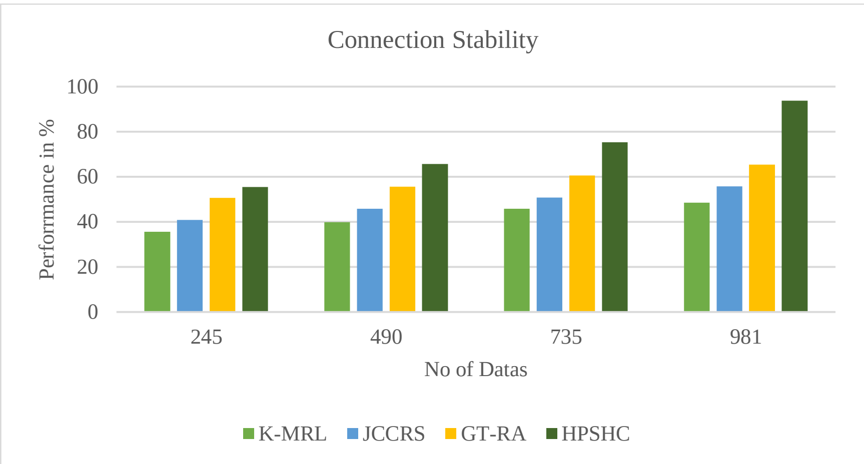

Fig. 12. Analysis of Connection Stability

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Figure 12 and Table 12 show that the obtained is K-MRL 85%, JCCRS 88%, GT-RA 90% and HPSHC 94%. The current systems have a high rate of failures due to disconnections in high mobility and heavy traffic. K-MRL learns gradually and GT-RA cannot learn as the topology changes. HPSHC is a stable connection through the application of optimized resources distribution with predictive handover control.

A. *Discussion Process*

The current systems with cyber threat detection depend mostly on the traditional machine learning and deep learning algorithms like ML-AIDS, ANN, and PCA, which are unable to process the noisy, imbalanced, and high-dimensional network traffic data. Such strategies tend to have limited capability to model temporal dependencies, behavior variability, and causal relationship between network entities and therefore have lower detection accuracy, higher false alarm rates and limited predictability. The suggested workflow provides these shortcomings, as it includes AA-CDR to provide adversarial-aware noise suppression and data refinement, which will guarantee the sound preprocessing of network traffic. Later on, both the short and long term sequential traffic behaviors are captured using the QETBM to facilitate the effective learning of the patterns of the temporal pattern. CE-FS module optimally selects features by saving features that are pertinent to an attack, and discarding redundancy, enhancing the efficiency of a classification. Lastly, GCARC uses graph-based reasoning to categorize sophisticated cyber-attack scenarios, whereas PCTIE adds proactive threat prediction capabilities to the framework to allow detecting the changing and unknown attacks at an early stage of their progression.

V. CONCLUSION

To sum up, the suggested hybrid cyber security system with AA-CDR, QETBM, CE-FS, GCARC, and PCTIE is much more efficient in terms of detecting, classifying, and predicting cyber threats than the current systems like ML-AIDS, ANN, PCA, K-MRL, JCCRS, and GT-RA. The framework is successful in managing adversarial and noisy network traffic with attack-aware preprocessing, temporal and behavioral dependencies with QETBM and selecting causally optimal features with CE-FS, which lead to better learning efficiency and reduce redundancy. According to experimental findings, there is significant improvement in the performance by Detection Accuracy of 96.8%, Precision of 95.7%, Recall of 94.9%, and F1-Score of 95.3% that points to reliable multi-class attack detection. False Positive Rate decreases by 33.2 % and Attack Classification Rate of 97.1% validates further refractions of the attack types. Also, a Feature Reduction Ratio of 48.5 and a Computational Time reduction of 37.2% indicate the efficiency of the proposed workflow. The PCTIE module also has a Threat Prediction Accuracy of 95.9 % that allows the improvement of proactive threat intelligence. Despite its effectiveness, the burden on computation that comes with large-scale networks, however, is still a problem that encourages future research on the lightweight, distributed, and adaptive security models.

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