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A method for adaptive replication and data migration in heterogeneous networks with a dynamic structure

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ABSTRACT

The relevance of this research lies in resolving the conflict between ensuring high availability and integrity of information and the resource constraints (power consumption, memory capacity, bandwidth) of mobile terminals in a heterogeneous network with a stochastically varying topology. Traditional approaches based on distributed hash tables, static replication, and NoSQL databases are limited by high communication overhead, degradation of routing during frequent connection drops, and an inability to proactively predict environmental dynamics, which necessitates the development of effective mathematical and software solutions for storing structured data. **The goal of this work** is to improve the availability, semantic integrity, and energy efficiency of structured data storage in heterogeneous networks with a dynamic structure by developing a hybrid model of adaptive replication controlled by a Deep Q-Network. To achieve this goal, **the** following **tasks** have been set: to formalize the access cost objective function, taking into account the resource parameters of mobile nodes; to develop a method for adaptive data replication and migration in the form of a machine learning pipeline optimized for deployment on edge devices; to develop the topology of a Deep Q-Network for adaptive control of the placement, migration, and competitive replacement of replicas in a stochastic topological environment. **The research methods** are based on the theory of Markov decision processes, reinforcement learning algorithms, and methods of mathematical statistics for analyzing data drift. **The results of this work** include the formalization of a method for adaptive replication of structured data guided by a neural network model based on criteria of expected channel lifetime and weighted demand, as well as the development of a machine learning pipeline using deep reinforcement learning algorithms optimized for deployment on edge devices. An experimental study of the developed solutions on a simulation platform using spatiotemporal real-world mobility datasets demonstrated that the proposed method maintains a query delivery success rate of eighty-three point nine percent at node speeds of up to one hundred kilometers per hour (compared to forty-six point nine percent for static replication and forty-one point one percent for Bamboo DHT), reduces the average search time by fifty-eight percent (from two hundred seven milliseconds to eighty-seven milliseconds), reduces communication energy consumption by thirty percent, and decreases the number of storage rewriting cycles by fifty percent. **The findings** confirm the high effectiveness of using DRL orchestration to ensure a controlled inconsistency regime under conditions of spatial isolation of network segments. **The scientific novelty** of the obtained results lies in the development of a method for adaptive replication of structured data in heterogeneous networks with a dynamic structure by continuously determining the replication coefficient and the optimal nodes for placing data copies based on the prediction of node trajectories and the level of their hardware and energy resources. The practical significance lies in the adaptation of an optimized machine learning pipeline, which enables the direct implementation of the model in autonomous transportation, environmental monitoring sensor networks, and emergency response systems.

Keywords: Distributed systems; edge computing; mobile ad hoc networks; structured data; adaptive replication

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INTRODUCTION

The paradigm of Mobile Edge Computing (MEC) and Fog Computing serves as the key technological foundation for modern Internet of Things (IoT) infrastructure, cyber-physical systems, and autonomous transportation. Shifting information processing and storage functions closer to the network edge makes it possible to significantly minimize network latency, reduce the load on backbone communication channels, and ensure the local autonomy of end terminals [1], [2], [3].

In deployment scenarios for intelligent transportation systems (ITS), unmanned robotic groups, and monitoring systems for man-made zones, mobile devices are organized into decentralized dynamic networks of the MANET (Mobile Ad-hoc Networks) and VANET (Vehicular Ad-hoc Networks) classes [2], [3].

The specific nature of such systems' operation gives rise to a number of fundamental scientific and technical challenges:

– the constant spatial mobility of nodes generates unpredictable changes in topology and frequent disruptions in wireless links;

– mobile terminals operate under conditions of limited local power supplies, restricted memory capacity, and unstable radio channel bandwidth;

– context-dependent structured data used by application services (spatial coordinates, motion vectors, sensor telemetry parameters, graph connections in the urban environment) require strict preservation of semantic integrity and accuracy during exchange between nodes.

Loss of connection to centralized cloud servers leads to database desynchronization or complete unavailability of critically important contextual information. A fundamental conflict arises between the need to ensure high availability (A) and integrity (I) of structured data sets and the strict hardware constraints of mobile nodes regarding power consumption (E_{lim}), storage capacity (M_{lim}), and channel bandwidth (B_{lim}) under conditions of stochastically varying topology [1].

Resolving this contradiction requires a transition from classical static models to intelligent hybrid systems for storing structured data, capable of dynamically adapting replication parameters in accordance with the predicted state of the network environment.

LITERATURE REVIEW

An analysis of modern distributed storage systems reveals significant limitations when they are directly ported to heterogeneous mobile edge environments. Distributed file systems (in particular, Apache HDFS) rely on an architecture with a dedicated metadata coordinator (NameNode) and a fixed block replication factor, which in dynamic MANET networks creates a critical vulnerability to a single point of failure [4], [5]. Distributed NoSQL systems (Apache Cassandra, MongoDB) implement decentralized ring sharding and eventual consistency via Gossip protocols; however, their fault-detection mechanisms incur significant overhead for control traffic transmission over low-bandwidth wireless channels. The use of blockchain-based storage systems (Hyperledger Fabric, Ethereum) ensures cryptographic resilience and immutability of the transaction history; however, the high computational complexity of consensus algorithms, the substantial size of the transaction ledger, and the long delay in record finalization make them unsuitable for power-constrained mobile devices operating in real time [6].

Distributed hash tables (DHTs) occupy a special place in decentralized architectures. Algorithms such as Chord or Bamboo organize a logical space of identifiers, where query routing is performed in O($logn$) logical steps. However, in the physical MANET environment, each logical step translates into 3–5 transit transmissions over physical radio links. When nodes travel at speeds exceeding 40–60 km/h, routing tables become outdated faster than the background procedures for stabilizing them can complete, leading to an exponential increase in the proportion of lost requests [7], [8]. To address these issues, a promising approach is the transition to semantic standards for context description, specifically JSON-LD (JavaScript Object Notation for Linked Data) and ETSI NGSI-LD [9]. These standards are based on the concept of a property graph, where information entities are linked by formalized semantic relationships [10]. This enables intelligent data fragmentation: critical metadata and semantic relationships can be separated from heavy static content and replicated with higher priority. In combination with the paradigms of Software-Defined Networking (SDN) and Software-Defined Storage (SDS), this allows central management of peripheral memory pools as a single space at the logical level, thereby overcoming the hardware heterogeneity of mobile platforms.

RESEARCH PROBLEM STATEMENT

A mobile heterogeneous peripheral network is modeled as a dynamic undirected graph $G_2(t) = \langle V(t), E(t) \rangle$, where $V(t) = \{v_1, v_2, \dots, v_n\}$ is the set of mobile and stationary nodes, and $E(t) = \{(v_i, v_j)\}$ is the set of active line-of-sight wireless channels at time t.

Each node $v_i \in V(t)$ is characterized by a resource vector:

$$\mathbf{R}_i(t) = \langle B_i(t), B_{\max}, \lambda_i, C_i, C_i^{free}(t), \mathbf{p}_i(t), \mathbf{u}_i(t) \rangle, \quad (1)$$

where $B_i(t)$ is the remaining battery energy level; $B_{\max}$ is the nominal capacity; λ_i is the discharge rate during computation and transmission; C_i is the allocated storage quota within the SDS pool; $C_i^{free}(t)$ is the current amount of free memory; $\mathbf{p}_i(t) = (x_i(t), y_i(t))$ are the spatial coordinates; and $\mathbf{u}_i(t) = \left(v_{xi}(t), v_{yi}(t)\right)$ is the node's current velocity vector.

Structured data is described using the graph-based semantic model of the NGSI-LD standard:

$$G_1 = \langle V_{data}, E_{data}, P_{data}, R_{data} \rangle, \quad (2)$$

where V_{data} is the set of entities; E_{data} represents the semantic relationships between entities; P_{data} denotes attribute properties; and R_{data} consists of metadata for properties and relationships.

The data set is fragmented into discrete information objects $O = \{o_1, o_2, \dots, o_m\}$. The spatial layout of an object o_k is described by a subset of carrier nodes $\mathcal{R}(o_k, t) \subseteq V(t)$.

To predict topology breaks, the expected link lifetime ($Link\ Expiration\ Time,\ LET$) between nodes v_i and v_j, which share a common antenna range r, is calculated as follows:

$$LET_{i,j}(t) = \frac{-(ab+cd)+\sqrt{(a^2+c^2)r^2-(ad-bc)^2}}{a^2+c^2}, \tag{3}$$

where the relative displacement and velocity coefficients are given by:

$$a = v_{xi} - v_{xj}, \quad b = x_i - x_j, \quad c = vy_i - vy_j, \quad d = y_i - y_j. \tag{4}$$

The intensity of demand for an information object is modeled by the weighted number of requests ($Weighted\ Access\ Count,\ WAC$), which penalizes energy-degraded terminals:

$$WAC_{i,k}(t) = AC_{i,k}(t) \cdot \left(\frac{B_i(t)}{B_{\max}}\right)^{\alpha}, \tag{5}$$

where $AC_{i,k}(t)$ is the empirical number of access operations over the interval Δt, and $\alpha \geq 1$ is the nonlinear penalty coefficient.

The lifecycle management of local replicas on nodes is based on the dynamic freshness coefficient $V_i(o_k, t)$ within the framework of the competitive aging procedure [11]:

$$V_i(o_k, t) = V_i(o_k, t_{last}) \cdot e^{-\gamma(t - t_{last})} + \ln(f_i(o_k) + 1), \tag{6}$$

where t_{last} is the time of the last request; $\gamma > 0$ is the time discount factor for value; $f_i(o_k)$ is the frequency of requests within the window Δt.

The semantic integrity of data received from third-party nodes is verified without transmitting the plaintext array using an interactive zero-knowledge proof (ZKP) scheme based on a modified Schnorr protocol [12]:

$$T - RES = (r_2 - r_1)M, \tag{7}$$

where T is the auditor's challenge; RES is the response from the carrier node; r_1, r_2 are the secret masking factors of the end terminal; M is a block of structured data.

The global optimization objective is to select a replica placement configuration $\mathcal{R}(o_k, t)$ that minimizes the total access cost and time delays while guaranteeing the system's reliability requirements:

$$\min_{\mathcal{R}(o_k,t)} F(t) = \sum_{k=1}^{m} \sum_{i=1}^{n} WAC_{i,k}(t) \cdot \min_{v_j \in \mathcal{R}(o_k,t)} \left[h(v_i, v_j) \cdot E_{tx} + \beta \cdot L(v_i, v_j)\right], \tag{8}$$

subject to the following constraints:

$$\sum_{o_k \in \mathcal{S}_i} \text{size}\,(o_k) \leq C_i, \quad \forall v_i \in V(t), \tag{9}$$

$$B_i(t) \geq B_{crit}, \quad \forall v_i \in V(t),$$

$$A(t) \geq A_{\min}, \quad I(t) \geq I_{\min},$$

where $h(v_i, v_j)$ is the path length in physical hops between nodes; E_{tx} is the specific energy per packet transmission; $L(v_i, v_j)$ is the end-to-end network delay; β – weighted delay priority coefficient; $\mathcal{S}_i$ – set of memory blocks v_i; B_{crit} – critical threshold of residual charge; $A(t)$ and $I(t)$ – system coefficients of availability and data integrity.

RESEARCH OBJECTIVES AND TASKS

The goal of this work is to improve the availability, semantic integrity, and energy efficiency of structured data storage in heterogeneous networks with a dynamic structure by developing a hybrid adaptive replication model controlled by a Deep Q-Network (DQN).

To achieve this objective, the following scientific and applied tasks have been formulated:

– to formalize the access cost objective function, taking into account the resource parameters of mobile nodes;

– to develop a method for adaptive data replication and migration in the form of an end-to-end machine learning pipeline optimized for quantization, deployment, and continuous monitoring of DRL models on edge devices;

– to justify and develop a DQN neural network topology for adaptive, preventive control of the placement, migration, and competitive replacement of replicas in a stochastic topological environment;

– to conduct an experimental study of the developed solutions on a simulation platform using spatiotemporal real-world mobility datasets and compare performance metrics with traditional static replication and DHT models.

The proposed approach consists of two parts: the development of a model for adaptive replication of structured data based on a DQN neural network and the LET and WAC metrics, and the development of a supporting infrastructure that includes a software-defined layer (SDN/SDS), a semantic model (NGSI-LD), and a machine learning engineering pipeline for deploying the model on edge devices.

METHOD FOR ADAPTIVE DATA REPLICATION AND MIGRATION

To improve the availability, semantic integrity, and energy efficiency of structured data storage in heterogeneous networks with a dynamic structure, this paper proposes a method for adaptive replication of structured data. The method involves using a hybrid model of adaptive replication of structured data controlled by a neural network, which determines replication coefficients and optimal nodes for placing data copies based on predictions of node trajectories and the level of their hardware and energy resources.

Implementing this method for storing structured data requires deploying a machine learning pipeline with the addition of a number of auxiliary components to adapt to heterogeneous edge platforms.

1. Architecture of the Edge Machine Learning Pipeline

The machine learning pipeline serves as the engineering foundation for deploying the proposed method on resource-constrained edge devices. Its effectiveness is confirmed by the following metrics.

In addition to standard operations, the pipeline incorporates the following specialized stages for structured data processing:

– quantization to reduce resource consumption—specifically, model memory size and inference time—enabling real-time decision-making without traffic delays;

– data drift monitoring (KS-test) to improve accuracy: automatic triggering of model retraining upon detection of drift based on the Kolmogorov–Smirnov criterion (D_{crit}> 0.05).

The pipeline consists of several interconnected processing stages.

1. *Telemetry collection and transformation stage (Telemetry system).* Local software agents on mobile devices measure remaining battery power$B_i(t)$, memory usage$C_i^{free}(t)$, radio metrics RSSI/SNR, and the frequency of access to semantic objects$AC_{i,k}$. These metrics are transmitted to the SDN controller via lightweight gRPC or MQTT messages at 500 ms intervals. At the SDN level, a Feature Store module (based on Feast) generates state vectorss_t and buffers transitions$\langle s_t, a_t, r_t, s_{t+1} \rangle$.

2. *Continuous Training Pipeline.* A centralized or clustered OpenDaylight SDN controller periodically retrains the D3QN model in the TensorFlow 2.x framework when the PER buffer accumulates more than10^5 new transition records. Computational parallelization is provided by Horovod/Ray.

3. *Quantization and Peripheral Optimization Stage (Model Compression & Edge Optimization).* The trained neural network is converted using the TensorFlow Lite toolkit:

– full 8-bit integer post-training quantization (INT8) is applied. This reduces the size of the binary model file by 74.2 % (from 1.18 MB to 305 KB) and lowers the node's RAM requirements during inference;

– weight pruning is performed, achieving 40% thinning, which minimizes the number of floating-point operations (FLOPS);

– the model is compiled into the FlatBuffer format, which is compatible with microcontrollers and lightweight runtime environments (TFLite Micro, ONNX Runtime Edge).

4. *Delivery and Deployment Phase (CI/CD Edge Inference).* The finished model file is distributed to edge controllers via automated pipelines (GitLab CI / Docker Registry) and integrated as a decision-making plugin into Open vSwitch (OVS) switches. The single-pass execution time (inference) of the optimized model on an ARM Cortex-A53 peripheral processor is 1.8 ms, ensuring timely generation of replication commands.

5. *Data Drift Monitoring Phase (Model & Data Drift Governance).* A monitoring system based on Prometheus and Grafana analyzes the statistical distributions of input state vectorss_t . If a discrepancy is detected using the two-sample Kolmogorov-Smirnov test ($D_{crit} > 0{,}05$) between the current distribution of

speeds/LET and the training sample, data drift is recorded, which initiates an automatic trigger for a model retraining cycle using current telemetry data.

The architecture of the Edge MLOps Pipeline for the proposed hybrid structured data storage model is designed to support the full lifecycle of the reinforced deep learning model (D3QN): from the aggregation of distributed telemetry in a dynamic topology to low-latency inference on resource-constrained edge devices and automatic retraining in the event of environmental drift.

Fig. 1 shows a structural and functional diagram of the Edge MLOps Pipeline architecture for a hybrid model of adaptive data storage and replication, presented as interconnected functional blocks and information flows.

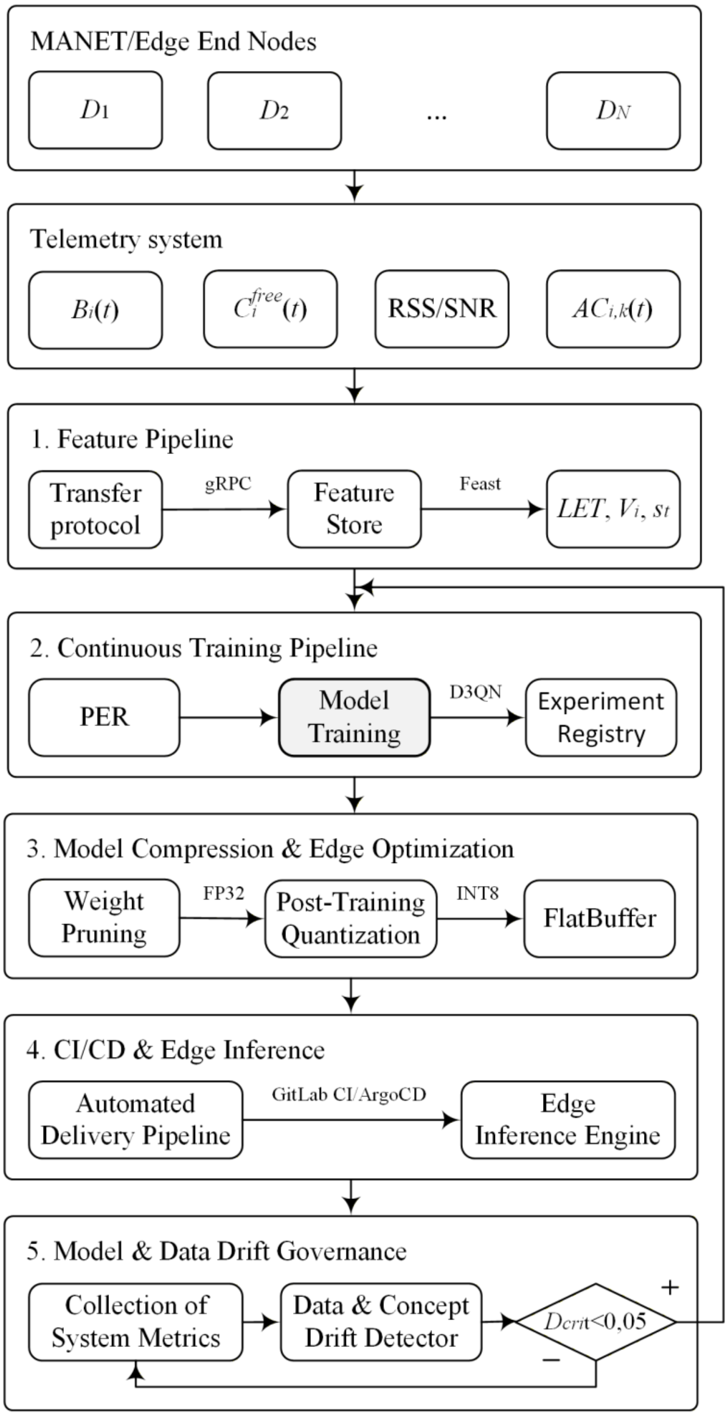

Fig. 1. **Structural diagram of an edge machine learning pipeline**
Source: **compiled by the authors**

The choice of a neural network architecture for managing data replication and migration in dynamic heterogeneous networks (MANET/VANET, MEC) is determined by the specifics of the environment: the stochastic nature of topology changes, the limited computational and energy resources of mobile terminals, and the need for real-time decision-making [13].

2. Justification of the neural network architecture for controlling adaptive data replication

The problem of adaptive replication in MANET/VANET belongs to the class of NP-hard problems in online combinatorial optimization in non-stationary environments.

Classic cache eviction algorithms (LRU, LFU, GREEDY-LET) are based on static rules and reactive behavior. They are unable to assess the long-term effect of replica migration – for example, the energy cost incurred now to avoid data loss at some point in the future. Another approach based on integer linear programming methods requires recalculating the optimum at every step of topology change, which has a computational complexity of $O(2^N)$ and is unacceptable for real-time applications (<50 ms). Tabular Q-learning also has a drawback: it requires discretization of the continuous state space, which leads to the "curse of dimensionality."

Decision-making regarding migration, the creation of new replicas, or the displacement of obsolete objects is formalized as a Markov Decision Process (MDP) [14], described by the tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma_{DRL} \rangle$.

The state space $\mathcal{S}$ is formed by the 8-dimensional vectors $s_t \in \mathcal{S}$, which is continuously generated by the SDN controller for each object o_k and candidate node v_i :

$$s_t = \left[\frac{B_i(t)}{B_{\max}}, \frac{C_i^{free}(t)}{C_i}, \frac{\min\limits_{j \in \mathcal{N}_i} LET_{i,j}(t)}{LET_{\max}}, \frac{WAC_{i,k}(t)}{\max\limits_j WAC_{j,k}}, V_i(o_k, t), \frac{h(v_i, \text{Center}_c)}{h_{\max}}, \frac{|\mathcal{N}_i(t)|}{|\mathcal{N}|_{\max}}, \overline{SNR}_i(t) \right], \tag{10}$$

where $\mathcal{N}_i(t)$ is the set of active neighbors of node v_i ; Center_c is the topological centroid of a stable cluster, and $\overline{SNR}_i(t)$ is the averaged signal-to-noise ratio in the communication channels.

The agent's action space $\mathcal{A}$ contains 4 discrete control operations:

– a^0 (Hold) – preserving the current storage configuration unchanged;

– a^1 (Replicate) – replicating the object o_k to the most energy-stable neighboring node $v_j \in \mathcal{N}_i$;

– a^2 (Migrate) – proactively moves the replica from the node v_i to the node v_j , followed by the deletion of the original at v_i before the connection is lost;

– a^3 (Evict) – forced eviction of the object with the lowest value of the coefficient $V_i(o_k, t)$ upon reaching the free memory limit $C_i^{free} \le C_c$.

The reward function R incentivizes an increase in the probability of data delivery and a reduction in latency while penalizing energy overconsumption [15]:

$$R(s_t, a_t) = w_1 \cdot \Delta A(o_k) - w_2 \cdot \frac{L(s_t, a_t)}{L_{\max}} - w_3 \cdot \frac{E_{cost}(a_t)}{E_{\max}} - \Psi(s_t, a_t), \tag{11}$$

where $\Delta A(o_k)$ is the increase in object availability; $L(s_t, a_t)$ is the measured access delay; $E_{cost}(a_t)$ is the energy cost of radio transmission of blocks, and $\Psi(s_t, a_t)$ is the penalty barrier function for violating the conditions $B_i(t) < B_{crit}$ or $C_i^{free}(t) < 0$. The weight coefficients are normalized: $w_1 + w_2 + w_3 = 1$.

Transition rules and constraints. The transition $s_t \rightarrow s_{t+1}$ is determined by the stochastic mobility function of *LET* nodes, the dynamics of *WAC* request generation, and the energy costs of radio transmission. If action a_t leads to a violation of the constraints ($B_i(t) < B_{crit}$ or $C_i^{free}(t) \le 0$), the state transitions to a terminal penalty state with the episode reset.

Action Selection Policy and Convergence. The decision-making strategy is ϵ -greedy with decay:

$$\epsilon_t = \max(\epsilon_{\min}, \epsilon_{\text{start}} \cdot \rho^t). \tag{12}$$

The convergence criterion is the stabilization of the average $\overline{R}$ payoff over a window of 500 episodes with a fluctuation of $\Delta\overline{R} < 1\%$, as well as the minimization of the loss function $\mathcal{L}(\theta) < 10^{-4}$.

To prevent systematic overestimation of Q-values in a stochastic environment, the Dueling Double Deep Q-Network (D3QN) architecture is used.

The neural network separates the estimation of the overall value of the environment state $V(s)$ from the specific advantage of each individual action $A(s, a)$:

$$Q(s, a; \theta, \alpha_v, \beta_a) = V(s; \theta, \alpha_v) + \left(A(s, a; \theta, \beta_a) - \frac{1}{|\mathcal{A}|} \sum_{a' \in \mathcal{A}} A(s, a'; \theta, \beta_a) \right), \tag{13}$$

where θ are the generalized parameters of the convolutional/fully connected layers; α_v and β_a are the specific weights of the state estimation and preference function flows, respectively.

3. Comparative Analysis of Datasets for Training a Neural Network Model

To ensure high generalization ability and reliability in training the DQN algorithm, a detailed study of four benchmark spatio-temporal mobility datasets was conducted.

The CRAWDAD epfl/mobility dataset contains the movement coordinates of taxis in the San Francisco area and is a classic benchmark for routing tasks in highly dynamic VANET networks. Its advantage lies in the presence of prolonged phases of synchronized movement of vehicle groups along highways, which allows for the study of the formation of stable spatial clusters. A drawback is the stochastic irregularity of the timestamps (ranging from 30 to 120 seconds), which required prior spline interpolation of the trajectories to synchronize them with a simulation step of 500 ms.

The EUA (Edge User Allocation) dataset details the locations of edge servers and mobile clients in Melbourne's business district. This dataset is the standard for modeling memory constraints C_i and the spatial redistribution of computational tasks, but it does not contain direct migration trajectories of D2D nodes between each other.

The T-Drive dataset covers over 15 million mobility points in Beijing and provides a substantial sample for offline training of deep neural network layers; however, the average interval between records of 177 seconds obscures the microdynamics of radio interference.

The CRAWDAD roma/taxi dataset records coordinates at a high sampling rate (every 7 seconds), which enables a direct analytical calculation of the $LET_{i,j}$ metric based on the velocity vector; however, the relatively small number of agents limits the variability of topological scenarios.

For the simulation experiment, the CRAWDAD epfl/mobility hybrid trajectory synthesis was applied, coupled with a spatial model of peripheral nodes according to the EUA specification.

ORGANIZATION OF EXPERIMENTAL STUDIES

1. Setup of the Simulation Experiment

To experimentally evaluate the effectiveness of the developed hybrid model, a combined simulation environment was created based on the Mininet-WiFi emulator, the OpenDaylight SDN software controller, and the TensorFlow neural network module.

The topology includes 50 mobile nodes that interact in direct ad-hoc wireless mode via the IEEE 802.11g/p protocol, with a radio signal transmission radius of $r = 250$ m within an area measuring 2000×2000 m.

The topology dynamics were modeled using a combination of a stochastic Random Waypoint model and a Manhattan Grid model, with device maximum speeds ranging from 10 km/h (pedestrian movement) to 100 km/h (vehicle movement on a highway). The total volume of the structured semantic repository consists of 500 NGSI-LD entities ranging in size from 2 to 50 KB.

To ensure high statistical reliability, each scenario was run 30 times, followed by the calculation of the standard deviation (SD).

The neural network model was implemented using the TensorFlow 2.x framework and has the following structural parameters:

– Input layer: 8 neurons (normalized state vector s_t);

– Hidden layer 1: A fully connected layer with 128 neurons using the LeakyReLU activation function ($\alpha_{leak} = 0{,}01$) and a batch normalization layer;

– Hidden layer 2: A fully connected layer with 64 neurons, using the ReLU activation function and a Dropout layer ($p = 0{,}15$) to prevent overfitting on monotonous trajectories;

– Value function stream $V(s)$: A fully connected layer with 32 neurons→ a linear scalar output of dimension 1;

– Reward function stream $A(s, a)$: A fully connected layer with 32 neurons→ and a 4-dimensional output layer (corresponding to the number of actions in $\mathcal{A}$).

Training is based on the Double DQN algorithm with Prioritized Experience Replay (PER). The target value y_t is calculated by decomposing the action selection and evaluation functions between the main (θ) and target (θ^-) networks:

$$y_t = R(s_t, a_t) + \gamma_{DRL}\, Q\left(s_{t+1}, \arg\max_{a'} Q(s_{t+1}, a'; \theta_t)\,;\, \theta_t^-\right). \quad (14)$$

Weight updates minimize the Huber loss function:

$$\mathcal{L}(\theta) = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}}\left[\mathcal{H}_\delta\left(y_t - Q(s_t, a_t; \theta)\right)\right], \tag{15}$$

$$\mathcal{H}_\delta(z) = \begin{cases} \frac{1}{2} z^2, & \text{if } |z| \leq \delta \\ \delta \cdot \left(|z| - \frac{1}{2}\delta\right), & \text{otherwise} \end{cases}, \quad for\ \delta = 1{,}0. \tag{16}$$

Parameter optimization is performed using the AdamW algorithm with an initial learning rate of$\alpha_{LR} = 0{,}0005$, an exponential decay of$\eta(t) = \alpha_{LR}/\sqrt{1 + 0{,}0001 \cdot t}$, a discount factor of$\gamma_{DRL} = 0{,}95$, and soft polyacc update for the target network$\theta^- \leftarrow \tau\theta + (1 - \tau)\theta^-$ with a rate of$\tau = 0{,}005$ at each step. Action space exploration is ensured by aε -greedy strategy with a decay of$\varepsilon(t) = \max(0{,}02,\ 1{,}0 \cdot 0{,}995^t)$.

The configuration and training parameters for D3QN are presented in Table 1. The simulation experiment parameters are presented in Table 2.

Table 1. **D3QN configuration and training parameters**

Parameter	Value	Description / Function
Dimension of the state vector s_t	8	Normalized values of the components of the vector s_t (10)
Action space cardinality $\lvert\mathcal{A}\rvert$	4	$\{a_0$:Hold, a_1:Replicate, a_2:Migrate, a_3:Evict $\}$
Discount factor γ_{DRL}	0.95	Priority of long-term rewards
Initial learning rate α_{LR}	0.0005	*AdamW* optimizer with decay 0*.0001t*
N_{PER}	10^5	α_{PER}= 0.6, β_{PER}= 0.4
Batch size	64	Number of iterations per gradient descent step
ϵ Greediness Parameters	$\epsilon_{start} = 1{,}0$; $\epsilon_{min} = 0{,}02$; $\rho = 0{,}995$	Exploration/exploitation balance
Target network update rate τ	0.005	$\theta^- \leftarrow \tau\theta + (1-\tau)\,\theta^-$

Source: **compiled by the authors**

Table 2. **Simulation experiment parameters**

Parameter	Value
Simulation environment	Mininet-WiFi 2.3.1, OpenDaylight (Helium), Python 3.11 / TensorFlow 2.21.0
Coverage area / Number of nodes	2000×2000 м /$N = 50$ mobile terminals
Wireless Standard / Frequency	IEEE 802.11g/p (DSRC/WAVE), $f = 5{,}9$ GHz
Radio Communication Range (r) / Transmitter Power	250 m /18 dBm (Log-Distance Path Loss Model,$\eta = 3.2$)
Channel bandwidth	6 ÷ 54 Mbps (dynamically dependent on SNR)
Mobility dataset / Movement model	CRAWDAD epfl/mobility + Manhattan Grid hybrid ($v = 10 \div 100$ km/h)
Number of semantic objects (m)	500 NGSI-LD JSON-LD files (size2 ÷ 50 KB)
Data query intensity (λ_{req})	Poisson traffic, $\lambda = 5$ req/s per node
Bamboo DHT baseline method conditions	Logical ring size:2^{16} ; stabilization timeout:1000 ms ; $k = 3$
Conditions for the Static Rep baseline method	Fixed replica placement ($k = 3$), without migration algorithms

Source: **compiled by the authors**

2. Assessment of Semantic Integrity and Conflict Resolution

To evaluate semantic consistency, we use the inconsistency coefficient metric$D_{inc}(t) \in [0,1]$, as presented in [14].

*Conflict scenario and its resolution***.** When a network segment is isolated, mobile nodes perform local write operations ("weak" consistency). After connectivity is restored, the SDN controller initiates an integrity verification procedure via the ZKP protocol (7) and resolves version conflicts based on Conflict-free Replicated Data Types (CRDT) for graph objects.

Experimental validation. When simulating 50 scenarios involving the disconnection and reconnection of network segments, the average duration of full synchronization and conflict resolution was420 ± 35 мс. The semantic integrity coefficient after connection restoration reaches100% , and in 98.2 % of cases, the ZKP audit successfully verified integrity without reanalyzing the entire data set.

3. Analysis of the Results

Data delivery reliability was assessed using the Data Availability Rate metric, defined as the ratio of the number of successfully executed requests with ZKP-verified integrity to the total number of requests generated within a fixed timeout period. The experimental results are presented in Table 3.

Table 3. **Evaluation of data delivery reliability using the data availability rate metric**

Node Movement Speed Scenario	Static Full Replication (%)	P2P DHT (Bamboo) (%)	Proposed hybrid model (%)
10 km/h (pedestrian movement, stable connection)	87.6 ± 1.8	92.6 ± 1.4	97.2 ± 0.6
20 km/h (local mobile traffic)	81.7 ± 2.4	86.3 ± 2.1	96.1 ± 0.8
60 km/h (urban traffic)	66.4 ± 3.8	62.8 ± 4.2	91.4 ± 1.2
100 km/h (high-speed highway)	46.9 ± 5.1	41.1 ± 5.8	83.9 ± 1.9

Source: **compiled by the authors**

Under low-speed conditions (10-20 km/h), all systems studied ensure high data availability (over 81-97 %). However, as speed increases to 100 km/h, the performance of classical approaches deteriorates rapidly: static replication retains only 46.9 % of successful queries due to replica carriers leaving the range, and the Bamboo DHT protocol drops to 41.1 % due to the loss of logical pointers in routing tables.

The proposed hybrid model based on DQN and semantic fragmentation maintains an availability rate of 83.9 %. A lower standard deviation ($SD = 1{,}9$ %) confirms the stability of the controller’s decision-making, as it proactively moves replicas to stable nodes before radio links are physically severed.

The evaluation of other system characteristics during the experiment is presented in Table 4.

Table 4. **Evaluation of system characteristics**

System characteristic under investigation	Static Replication	P2P DHT (Bamboo)	Proposed hybrid model
Average data search and delivery time (ms)	$139 \pm 12{,}4$	$207 \pm 18{,}7$	$87 \pm 4{,}2$
Algorithmic complexity of access	$O(1)$ (local) /∞ (gap)	$O(\log n)$ logical steps	Virtual$O(1)$ (SDS)
Service traffic volume (MB/hour)	$12{,}4 \pm 1{,}1$	$89{,}6 \pm 8{,}4$	$24{,}1 \pm 1{,}8$
Average energy consumption for communication (F)	Base level (0%)	Savings up to $15 \pm 2{,}8$ %	Savings up to $30 \pm 1{,}5$ %
Number of flash memory rewrite cycles	100 % (LRU baseline)	135 % (degradation)	50% (competitive aging)
Response time to physical link failure	Re-initiation ($>$ 1200 ms)	DHT recalculation ($>$ 500 ms)	SDN switching ($<$ 15 ms)

Source: **compiled by the authors**

An analysis of timing metrics shows that the Bamboo DHT protocol introduces significant delays (averaging 207 ms) due to the need to sequentially query intermediate nodes.

In the proposed model, the response time is reduced to 87 ms (a 58.0 % improvement), since the SDN controller has global information about the topology and routes the request directly to the physically closest carrier node.

The volume of service traffic in the developed model is 3.7 times lower than in DHT (24.1 MB/h versus 89.6 MB/h), since telemetry is transmitted centrally with a 500-ms sampling interval, rather than through continuous broadcast exchange of state tables.

The energy savings of the proposed model reach 30.0 % compared to static schemes thanks to the use of the “WAC ” metric, which prevents the transmission of replicas to nodes with low residual charge.

Furthermore, the use of the competitive aging algorithm $V_i(o_k, t)$ reduces the number of write cycles to the flash memory of mobile devices by 50.0 % compared to greedy strategies such as LRU, which significantly extends the service life of hardware storage devices.

A study of the method's robustness as node density varies from $N = 20$ (sparse network) to $N = 100$ (high-density network) showed that the proposed model maintains data availability above $78{,}5$ % even under low-density conditions, whereas Bamboo DHT degrades to $34,2\%$. As the query load increases from λ=1 to λ=20зап/с , the average search time in the proposed model increases by only $14{,}2$ % (from 81 мс to $92{,}6$ мс), which indicates high algorithmic scalability.

DISCUSSION OF RESULTS

The gains achieved in terms of availability, latency, and energy efficiency can be attributed to three main architectural and algorithmic factors:

Software-Defined Storage (SDS). Abstracting the heterogeneous memory of physical nodes into a virtualized pool allows the SDN controller to route requests along optimal physical paths with the algorithmic complexity of a virtual $O(1)$, eliminating the need for multi-step logical transits in P2P DHTs.

Neural network-based mobility prediction via D3QN. The use of the expected link lifetime metric (LET) and the weighted access coefficient (WAC) enables the agent to initiate the migration of semantic objects preemptively, before the actual failure of the wireless channel.

A two-level semantic consistency model. The introduction of the concept of bounded inconsistency, with transactions classified as "strong" (within stable clusters) and "weak" (in disconnected domains) allows mobile applications to continue operating without interruption during temporary isolation of segments, with guaranteed deferred restoration of global consistency via ZKP audit.

The applicability of the proposed model is limited by network density parameters and the frequency of telemetry generation. The model demonstrates maximum efficiency when node density is at least 3–4 neighbors within each terminal's coverage radius ($|\mathcal{N}_i| \geq 3$).

In critically sparse environments (Delay-Tolerant Networks, DTN scenarios), the performance of the DRL agent deteriorates due to the lack of available alternative carriers for preventive migration, which necessitates a transition to adaptive epidemic routing protocols (Spray-and-Wait).

A comparison of the obtained results with current global research in the field of MEC confirms that the implementation of a combined approach integrating spatial mobility and DRL reduces information delivery delays by 17-25 % compared to non-integrated caching models, while ensuring high resilience to topological fluctuations.

CONCLUSIONS

This work addresses the scientific and applied problem of improving the availability, semantic integrity, and energy efficiency of structured data storage in heterogeneous networks with dynamic structures by developing a hybrid adaptive replication model controlled by a Deep Q-Network.

The topology of the Dueling Double Deep Q-Network with Prioritized Experience Replay, the *AdamW* optimizer, and the Huber loss function has been theoretically justified, allowing to optimize the lifecycle of replicas while accounting for the residual energy of devices, the expected link lifetime LET, and the demand profile WAC.

A peripheral machine learning pipeline has been designed that provides automated quantization of a neural network to the TFLite INT8 format (with a 74.2 % reduction in size to 305 KB and an inference time of 1.8 ms on the ARM architecture), as well as tracking data drift using the Kolmogorov–Smirnov test.

Numerical and experimental studies confirmed that the proposed model maintains a data availability rate of 83.9 % at node movement speeds of up to 100 km/h (compared to 41.1% in DHT Bamboo), reduces the average search time from 207 ms to 87 ms (by 58.0 %), reduces communication energy consumption by 30.0%, and decreases the number of storage rewriting cycles by 50.0 %.

A promising direction for further research is scaling the developed methods based on Federated Multi-Agent DRL to eliminate the need for centralized telemetry transmission to SDN controllers and integrating the architecture into wireless networks.

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Метод адаптивної реплікації та міграції даних в гетерогенних мережах з динамічною структурою

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АНОТАЦІЯ

Актуальність дослідження полягає у розв'язанні протиріччя між забезпеченням високої доступності та цілісності інформації і обмеженнями ресурсів (енергоспоживання, обсяг пам'яті, смуга пропускання) мобільних терміналів в умовах стохастично змінної топології гетерогенної мережі. Традиційні підходи на основі розподілених хеш-таблиць, статичної реплікації та NoSQL-сховищ обмежені високими накладними комунікаційними витратами, деградацією маршрутизації при частих розривах зв'язку та нездатністю до превентивного прогнозування динаміки оточення, що обумовлює розробку ефективного математичного та програмного забезпечення для збереження структурованих даних. **Метою роботи** є підвищення доступності, семантичної цілісності та енергоефективності збереження структурованих даних у гетерогенних мережах з динамічною структурою шляхом розвитку гібридної моделі адаптивної реплікації під управлінням нейронної мережі Deep Q-Network. Для досягнення цієї мети поставлено такі **завдання**: формалізувати цільову функцію витрат доступу з урахуванням ресурсних параметрів мобільних вузлів; розробити метод адаптивної реплікації та міграції даних у вигляді конвеєра машинного навчання, оптимізованого для розгортання на периферійних пристроях; розробити топологію нейронної мережі Deep Q-Network для адаптивного управління розміщенням, міграцією та конкурентним заміщенням реплік у стохастичному топологічному оточенні. **Методи дослідження** базуються на теорії марковських процесів прийняття рішень, алгоритмах глибинного навчання з підкріпленням та методах математичної статистики для аналізу дрейфу даних. **Результатами роботи** є формалізація методу адаптивної реплікації структурованих даних під керівництвом нейромережевої моделі за критеріями очікуваного часу життя каналу і зваженого попиту, а також розробка конвеєра машинного навчання, з використанням алгоритмів глибинного навчання з підкріпленням, оптимізованого для розгортання на периферійних пристроях. Експериментальне дослідження розроблених рішень на імітаційному стенді із використанням просторово-часових датасетів реальної мобільності довело, що запропонований метод утримує коефіцієнт успішності доставки запитів на рівні вісімдесят три цілих дев'ять десятих відсотка при швидкості руху вузлів до ста км/год (порівняно з сорока шістьма цілими дев'ятьма десятим відсотка для статичної реплікації та сорока одним цілим одним десятим відсотка для Bamboo DHT), скорочує середній час пошуку на п'ятдесят вісім відсотків (з двохсот семи мілісекунд до вісімдесяти семи мілісекунд), знижує енерговитрати комунікації на тридцять відсотків та зменшує кількість циклів перезапису накопичувачів на п'ятдесят відсотків. **Отримані висновки** підтверджують високу ефективність застосування DRL-оркестрації для забезпечення режиму контрольованої неузгодженості в умовах просторової ізоляції мережевих сегментів. **Наукова новизна** отриманих результатів полягає у розвитку методу адаптивної реплікації структурованих даних у в гетерогенних мережах з динамічною структурою шляхом неперервного визначення коефіцієнта реплікації та оптимальних вузлів розміщення копій даних на основі прогнозування траєкторій вузлів і рівня їхніх апаратно-енергетичних ресурсів. Практичне значення полягає в адаптації оптимізованого конвеєра машинного навчання, що уможливлює безпосереднє впровадження моделі в автономному транспорті, сенсорних мережах моніторингу довкілля та системах екстреного реагування.

Ключові слова: розподілені системи; периферійні обчислення; мобільні спеціалізовані мережі; структуровані дані; адаптивна реплікація

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