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An Intelligent and Personalized News Recommendation Model using Artificail Bee Colony Optimization-based Reinforcement Learning

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ABSTRACT

A personalized news recommendation system is a crucial and engaging area aimed at tailoring news content according to individual reading habits. Numerous research studies have been conducted over the years, resulting in significant advancements in predicting user behavior and enhancing user experience. Despite this progress, several challenges remain unresolved and demand further investigation. Traditional news recommendation systems follow a conventional approach to content delivery, which often lacks the adaptability required for long-term sustainability. This paper introduces a personalized, enriched news-feeding system that leverages a reinforcement learning approach integrated with the Artificial Bee Colony Optimization (ABCO) algorithm. The system recommends news based on a personalized wish list and commonly researched attributes in news content analysis. An agent node generates a list of recommended news items by gathering personal user information, while the environment evaluates and rewards recommendations based on the user's reading patterns. The agent node is developed using the ABCO algorithm, which facilitates the generation of enriched and relevant news suggestions. The performance of the proposed system, evaluated in terms of recommendation accuracy, is based on personalized data and has been compared against existing models. Experimental results show that the proposed system achieves an accuracy rate of 97.5% in news recommendation.

Keywords: Recommended System, Artificial Bee Colony Optimization, Reinforcement Learning, Personalized Learning, Agent Modelling.

INTRODUCTION

Digital content delivery has emerged as a powerful solution for disseminating information to a broader audience, and the Internet serves as the most efficient medium for achieving this. Online news distribution platforms have become highly popular, with 65% of online users preferring them over traditional media such as newspapers, television news, and printed publications. This shift is largely due to the convenience and real-time accessibility offered by digital news platforms, prompting a gradual transition among traditional news consumers toward digital alternatives [2]. Each day, news content creators publish a vast number of articles, making it nearly impossible for users to explore all available sources [3]. To address this challenge, personalized news recommendation systems tailor article suggestions based on individual user interests. These recommendation platforms are essential for enhancing the user's reading experience [4]. In recent years, such systems have gained significant attention from both academia and industry [3][5].

Figure 1 illustrates the workflow of a typical news recommendation system. News reading applications gather user behavior data, such as searches and preferences. A large news pool stores content from various sources. The system then selects relevant articles based on user interests and feeds them into the recommendation engine, which ranks and presents the most suitable news items. User profiles are continually updated based on interactions, refining the personalization process. Traditional recommendation systems are increasingly being replaced by these personalized environments. Extensive research is ongoing to address the challenges posed by this transition. Given the constant influx of new articles and the quick expiration of older content, news recommendation systems often face the cold-start problem. Modern articles typically contain rich textual and multimedia elements—titles, images,

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and detailed content—which are analyzed using advanced natural language processing techniques to interpret user preferences. However, most news platforms lack explicit user feedback mechanisms such as ratings or reviews. Consequently, user interest must be inferred from indirect interactions, such as article clicks. Designing truly personalized recommendation models remains a significant challenge due to the diverse and dynamic nature of user preferences. Solving this complexity requires innovative and effective approaches [6]. Numerous researchers have conducted comprehensive surveys of existing personalized news recommendation systems [8–18].

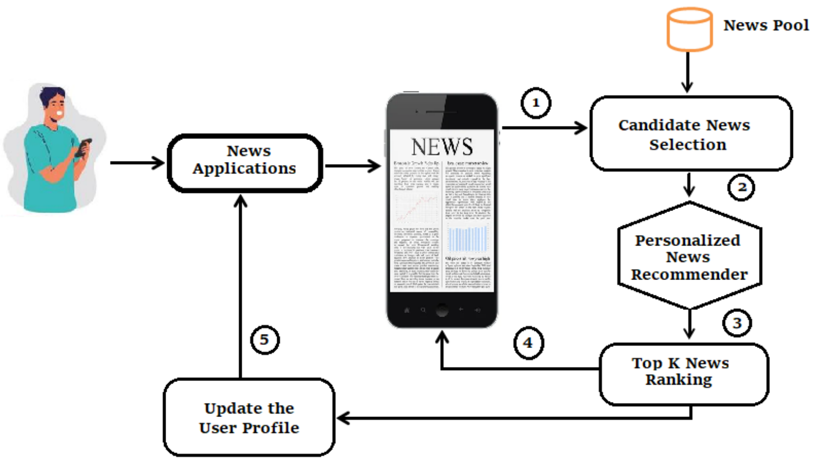

Figure 1: Generalized Working Principle of News Recommendation System

The Personalized News Recommendation System

Numerous online news platforms utilize personalized news recommendation techniques [19]. In contrast, non-personalized systems offer news suggestions based solely on general factors such as overall popularity [21–24], editorial choices [25], and user location [26, 27], without tailoring content to individual users [20]. Personalized recommendation systems are typically grouped into three main categories: collaborative filtering, content-based approaches, and hybrid models. Recently, content-based approaches have evolved to include traditional semantic techniques, contextual bandits, and deep learning-based models.

These personalized systems are trained to align with user preferences, considering both news categories and individual interests. However, news content becomes outdated rapidly and is continuously updated with new material, causing both news features and candidate articles to change dynamically. Additionally, a user's interest in reading specific news items may vary depending on their current mood. A general framework for personalized news recommendation using reinforcement learning is illustrated in Figure 2.

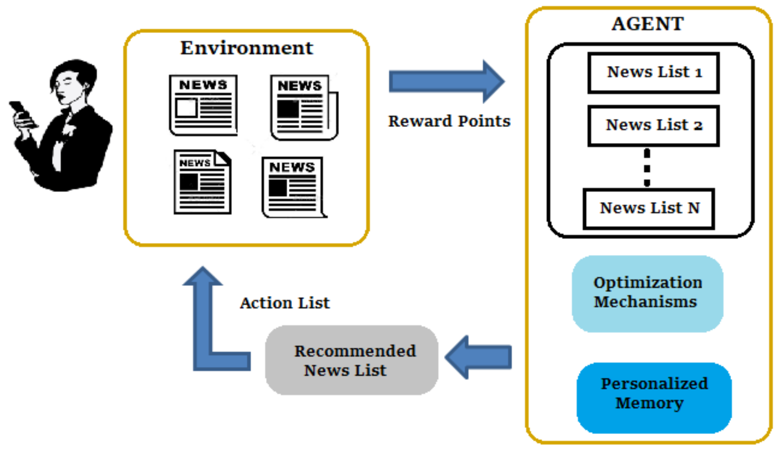

Figure 2: General Framework for Reinforcement Learning-based Personalized News Recommendation System

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For each new instance, the recommendation system presents a unique set of news categories tailored to the user's personalized memory profile. Optimization mechanisms aim to generate and deliver a curated news list, which serves as input to the environment for user selection. Reward points are then computed based on the user's choices from the recommended content. The agent refines the news selection strategy by considering both the criteria of the news items and the reward points provided by the environment. Online recommendation techniques continuously adapt to evolving news characteristics and shifting user interests through real-time updates, striving to maximize the reward points, particularly measured by the Click-Through Rate (CTR).

Research Gap

Current recommendation models face several challenges, which contribute to a growing disconnect between user preferences and the news content being suggested.

1. Most personalized recommendation systems rely heavily on reward mechanisms like Click Through Rate (CTR), limiting their adaptability.
2. While some systems incorporate user feedback beyond simple click or non-click indicators, which can enhance recommendation quality, there remains ambiguity regarding the selection of effective parameters for optimal system design.
3. Many existing models tend to produce monotonous results by consistently recommending similar types of news, which can reduce user engagement.
4. These models also struggle with optimization issues, often getting trapped in local or global optima when matching news content to users' personalized interests

Contributions

This paper introduces a personalized news recommendation system leveraging reinforcement learning techniques to deliver relevant and enriched news content to active readers. The key contributions of the proposed approach are as follows:

1. A reinforcement learning-based personalized news recommendation system is developed, utilizing the Artificial Bee Colony Optimization (ABCO) technique.
2. In this system, the agent identifies the reader's news interests and recommends news articles tailored to each individual's preferences.
3. The environment provides either positive or negative reward points based on sentiment scores derived from user clicks and feedback. The Artificial Bee Colony Optimization Algorithm updates the user interest list according to these reward signals.
4. Reward points are further refined using a richness score that includes the sensitivity score of news content. Each article is assigned a weight factor ranging from 0 to 1.
5. This weight factor enhances the freshness of the recommended content, leading to improved news diversity compared to traditional news recommendation systems.
6. The system is designed for dynamic adaptability, catering effectively to a wide range of readers with varying reading levels.

The rest of the paper is organized as follows: Section 2 reviews reinforcement learning-based news recommendation systems and highlights research gaps in current models. Section 3 elaborates on the proposed personalized recommendation framework. Section 4 presents the experimental results and analysis, while Section 5 concludes the paper and outlines future directions for personalized news recommendation research.

RELATED WORK

Wouter et al. [28] presented an extension for the existing Hermes framework based on the user profile to store terms or concepts found in the news items. Kompan et al. [29] proposed a content-based news

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recommendation system using a cosine-similarities searching mechanism with an effective representation of the news recommendations. They have performed experimentation for the proposed method with the environment of the largest electronic Slovakia newspaper. Li et al. [30] modeled a personalized news recommendation system based on a contextual bandit problem. This method sequentially selects news articles based on the contextual information about the user and articles in addition to this the selection system uses user click feedback to maximize total user clicks. Li et al. [31] proposed a two-stage personalized recommendation system based on the exclusive characteristics of news articles and user-inherited interest in the reading behavior of individuals. Liu et al. [32] developed a framework for predicting user current interest from the activities of that particular user. They have combined the concept of a content-based recommendation mechanism with collaborative filtering to create personalized recommendations for news articles. Lu et al. [33] proposed a framework based on a neural optimization technique for Partially Observable Markov Decisions and the author claims that the proposed method effectively uses collected historical data from the real-world environment and automatically achieves a suitable list of news articles. Xiangyu Zhao et al. [34] proposed a principle approach to create a set of complementary items and the corresponding strategy to display pages in 2-D and they have proposed novel page-wise recommendations based on deep reinforcement learning technique. This optimizes the page items with the proper display order based on the real-time feedback collected from the users. Lixin Zou et al. [35] introduced an RL framework to optimize by using Q-Network which is designed in a hierarchical LSTM to model the complex user behaviors and S-Network simulates the environment to assist with the Q-Network

Manoharan et al. [36] proposed a fuzzy logic-based approach for predicting the interest of the user and their categories by analyzing the implicit user profile. The viral news articles and their categories are analyzed through data mining social media feeds from Facebook and Twitter. Bangari et al. [37] presented a review of the different reinforcement algorithms, Deep Q Learning Network (DQN), Twin Delayed DDPG (TD3), and Deterministic Policy Gradient (DDPG) to design for the news recommendation system and also discussed challenges identified from the reinforcement recommendation systems. Kabra et al. [38] proposed a novel news recommendation system for providing a top k number of suggested lists of news based on context-aware recommendations The item features and user feedback will be used as input for the reinforcement learning backed dynamic algorithm

Song et al. [39] proposed a framework for a news recommendation system using deep Q-learning with double exploration networks. They have used an offline dataset and a new reward point calculation method in the proposed method. Guanjie et al. [40] proposed a news recommendation system using a Deep Reinforcement Learning framework and this method uses a Deep Q-Learning based recommendation system with explicit future reward points. Fangzhao et al. [41] presented a large scale dataset for news recommendation, known as MIND. This has been constructed from the user click logs from Microsoft News, The MIND dataset has 1 million users and contains more than 160K English news articles. Each entry is designed with rich textual content, News title, click and non-click counts, category of news, content

FUNDAMENTAL ALGORITHM METHODS

This section discussed the basic assumptions and fundamental ideas behind the artificial bee colony optimization algorithm

Assumption 1: The available news instances are mentioned as $AV_{news} = \{X_i, 1 \leq i \leq N\}$, here N represents the total number of news instances in the particular time interval. Each news instance is represented as follows,

$$X_i = \{T \leftarrow (News\ Attributes), Y \leftarrow (Set\ of\ keywords\ extracted\ from\ X_i), Category_{X_i}, \quad Sentiment_{Score}^{X_i}\}$$

Here $T_{X_i} \leftarrow \{x_i, 1 \leq i \leq n\}$and $Y_{X_i} \leftarrow \{y_j, 1 \leq j \leq m_1\}$. The $Category_{X_i}$ mentioned the list of categories covered by the news instant X_i.

Assumption 2: The sentiment score $Sentiment_{Score}^{X_i}$ for the news instant X_i is measured as follows,

$$SScore_Y^{X_i} \leftarrow \sum_{j=1}^{m_1} Avg_{Score}^{y_j} \quad \rightarrow (1)$$

$$Avg_{Score}^{y_j} \leftarrow \frac{\#(y_j)}{\sum(Words\ in\ X_i)} \quad \rightarrow (2)$$

Assumption 3: The news readers are commonly known as users U_k in the proposed method and the interest list for the particular user has been represented as follows $IL_{U_k} = \{Reading_{Categries}, Class_{U_k}, Keywords_{likes}^{U_k}\}$, the reading categories and liking keywords are created as follows,

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$$Reading_{Categries} \subseteq News^{s}_{Categories} \rightarrow (3)$$

$$Keywords^{U_k}_{likes} \subseteq News^{S}_{Keyword} \rightarrow (4)$$

The super set for news categories and keyword list is constructed as follows,

$$News^{s}_{Categories} \leftarrow \bigcup_{i=1}^{N} Category_{X_i} \quad \rightarrow (5)$$

$$News^{s}_{Keywords} \leftarrow \bigcup_{i=1}^{N} Y_i \quad \rightarrow (6)$$

Artificial Bee Colony Optimization Algorithms

The Artificial Bee Colony (ABC) Optimization Algorithm is a nature-inspired, swarm-based meta-heuristic technique. It is modeled after the foraging behavior exhibited by honey bees, as originally conceptualized by Tereshko and Loengarov [43], and inspired by the natural behavior of honey bee colonies [42]. The ABC algorithm consists of three fundamental components. The first two components simulate the roles of employed and onlooker bees, which are responsible for exploring and exploiting rich food sources to gather nectar. The third component comprises scout bees that carry out a random exploration process to discover new food locations.

In this algorithm, each solution within the search space corresponds to a set of optimization parameters representing food source positions. The number of employed bees is equal to the number of food sources, with each food source evaluated based on its fitness value, which indicates its quality and is tied to its position. Employed bees assess these sources and communicate the findings to the onlooker bees, enabling them to identify the most promising solutions. The population size—including employed bees, onlooker bees, and solutions—is kept constant and equal. The upcoming section elaborates on the different phases of the ABC algorithm

Initial Phase

Let $X = \{x_i\}, 1 \leq i \leq SN$ is the initialized population, which is generated randomly in the entire space. The food source x_{ij} in the initial phase is calculated as follows (equation 7),

$$x_{ij} = x_j^{MIN} + \alpha \times \left(x_j^{MAX} - x_j^{MIN}\right), 1 \leq i \leq SN \text{ and } 1 \leq j \leq D \rightarrow (7)$$

Employed Bees Phase

This phase is used to generate new solutions V_i by using a random neighborhood searching process over the available population x_i using the following equation (8),

$$V_{ij} = x_{ij} + \alpha \times \left(x_{ij} - x_{kj}\right) \rightarrow (8)$$

Here k and j are the randomly selected values from the SN (number of solution population) and D (dimensional vector) and the condition of $(k \neq i)$. If V_i produces an excellent result than x_i, x_i is replaced with V_i. The counter value will be reset or increased by 1 based on the result acceptance.

Onlooker Phase

This phase applies a selection probability to select food sources based on fitness ratio. The probability can be calculated as follows (equation 9),

$$Probability_i = \frac{Fitness_i}{\sum_{i=1}^{SN} Fitness_i} \rightarrow (9)$$

Then the fitness value for the food source x_i is calculated as follows (equation 4),

$$Fitness_i = \begin{cases} \dfrac{1}{1 + f(x_i)}, & if\ \ f\,(x_i) \geq 0 \\ 1 + |f\,(x_i)|, & Otherview \end{cases} \rightarrow (10)$$

From equations (9) and (10) it is easy to infer that the food source with the larger fitness value has the highest probability of being selected by the onlooker bees.

Scout Bee Phase

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The onlooker bees select their food sources randomly known as scouts. The employed bee's solutions could not be improved through a maximum number of trials (Maximum Limit or Abandonment Criteria) by the ABC algorithm

Algorithm 1: Artificial Bee Colony Optimization Algorithm
1. Generate Random Initial Populations by using the equation (7) 2. Compute Fitness value for each population $Fitness_{x_i}, 1 \leq i \leq SN$ 3. Initialize the counter $Counter = 1$ 4. Do a. For each employee bee from $E_{bee_i}, 1 \leq i \leq SN$ i. Compute V_{ij} using equation (8) ii. Compute Fitness value $Fitness_{V_i}$ iii. Apply Greedy Selection Process over x_i, V_i b. End For 5. Calculate the probability values $Probability$ for the solution x_i using equation (9) a. For each onlooker bee from $OL_{bee_i}, 1 \leq i \leq SN$ i. Choose a solution x_i with support of probability value of $Probability$ ii. Create a new solution V_j iii. Computes its fitness value $Fitness_{V_j}$ iv. Apply Greedy Selection Process over x_i, V_j b. End For 6. If an abandoned solution is attained then Replace it with a new solution (randomly produced by equation (10)) 7. Else No replace 8. The available list of best solutions keeps track and increments the counter 9. While $(Counter \leq Max_{iterations})$

PROPOSED NEWS RECOMMENDATION TECHNIQUE

This section discussed the proposed news recommendation system using a reinforcement learning model based on Artificial Bee Colony Optimization algorithms. Nature-inspired algorithms are a suitable solution for the semi-supervised learning environment and these algorithms work based on the concept of natural behaviour of living things. The proposed architecture for the news recommendation system is shown in Figure 3,

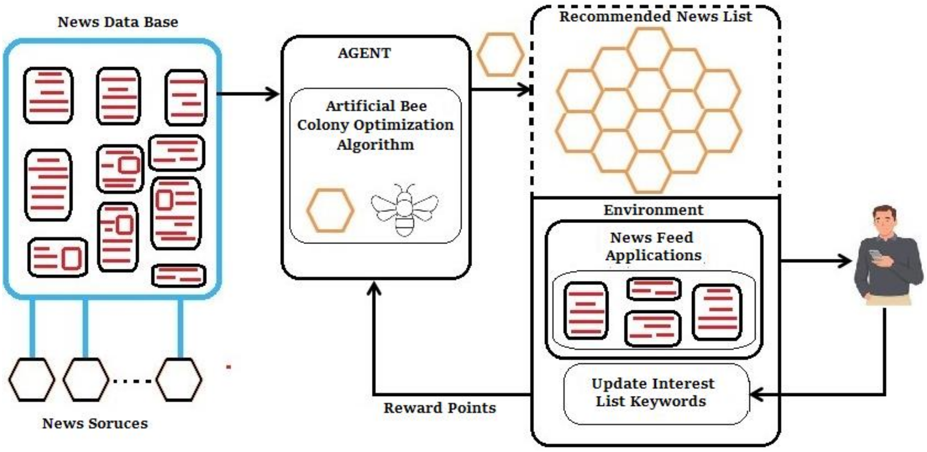

Figure 3: Proposed Architecture for the News Recommendation Method using Reinforcement Learning

In the proposed method, the agent has been designed based on the concept of an artificial bee colony optimization mechanism. The agent will create a recommended list of the news based on the personalized interest derived from the user behavior by using several clicks, the category of news likes, and the news searching category. This recommended news list will be given as input to the environment and the user selects news from this recommended list, based on the news selection reward points will be calculated.

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Proposed Reinforcement Learning Algorithm

This section discussed the proposed reinforcement algorithm for the personalized News recommendation method. The initial stage is constructed with recommended news feeds from the available news list and the news recommendations will be prepared based on ABC optimization technique. The following algorithm 1 explains the working principle of the proposed reinforcement learning algorithm

Algorithm 2: Proposed Reinforcement Learning Algorithm
1. The initial stage has been constructed based on the available list of news instances. The available list of news instances is indicated as $AV_{news} = \{X_i, 1 \leq i \leq N\}$, and each $X_i \in AV_{news}$ will be measured with the sentiment score $Sentiment_{Score}^{X_i}$ by using the equation (1). 2. The available news instances AV_{news} with sentiment score $Sentiment_{Score}^{X_i}$ for news instance will be given as Input for the Agent Node and apply ABC algorithm (***Algorithm 1***) for the initial stage of segmentation according to the sentiment score based on user interest (equation (3) and (4)). 3. The news readers interest list for a Learner U_k will be created as $IL_{U_k} = \{Reading_{Categries}, Class_{U_k}, Keywords_{likes}^{U_k}\}$ and this list will be updated based on equation (3) and equation (4) 4. Select a suitable and recommended list of news instances for the news reader U_k will be given as follows $$SRNList_{U_k}\{(X_j, [Click\ or\ Non - Clicked], Sentiment_{Score}^{X_i})\}_{j=1}^{M}$$ 5. Apply Artificial Bee Colony Algorithm-based generative AI model (**Algorithm 2**) over $SRNList_{U_k}$for selecting the enriched news article from this list 6. The enriched news instances are taking the top position in this list$ESList_{Course}^{l}$. 7. This recommended enriched news list$ESNList_{X_i}^{U_k}$ will be given as input for the Environment Node and the news reader will click and read the more suitable news instance from the$ESNList_{X_i}^{U_k}$list. 8. The newsreader interest listIL_{U_k} will be updatedbased on the news instance selection. 9. This process will return an Expected Reward point and this will be calculated as follows, $$ER_T = \sum_{i=0}^{T} \gamma^i Sentiment_{Score}^{X_{i+1}} \quad \rightarrow (11)$$ Here γ^iweight factors the particular course. The weight factors are assigned within the interval of [0, 1]

EXPERIMENTAL SETUP AND IMPLEMENTATION DETAILS

This section discussed the dataset, experimental setup, and performance evaluation. The experiment was conducted with the Microsoft News Dataset (MIND) [41]. MIND is a large-scale dataset of news recommendation systems and this has been collected from the anonymized behaviour of logs in Microsoft news website. This dataset contains 160k English news articles with more than 15 million impressions logs, which have been generated by 1 million users. Each impression log contains click and non-click events and historical news click behaviors of the user. The dataset contains four different file behaviors.tsv, news. tsv, entity_embedding.vec and relation_embedding,vec. The behaviors.tsv (Click History and impression logs of users) and news.tsv (information of news articles) files are taken for conducting the experiment.

The behaviors.tsv file contains the impression logs and user news click histories with five attributes, Impression ID, User ID, Time, History, and Impressions. The news.tsv file contains detailed information on news articles available in the behaviors.tsv file. This file has 7 attributes, News ID, Category, Sub Category, Title, Abstract, URL, Title Entities, and Abstract Entities

Performance Evaluation

The following evaluation metrics are used to evaluate the performance of the proposed method, Click Through Rate (CTR), Precision (P), and Normalized Discount Cumulative Gain (nDCG) [44]. The Equations (12), (13), and (14) are used to calculate the CTR, Precision, and nDCG values respectively,

$$CTR_{U_k} = \frac{\#Clicked\ News\ Items\ \in\ Recommended\ List}{\#\ News\ Items\ in\ the\ Recommended\ List} \quad \rightarrow (12)$$

$$P_{U_k}(T) = \frac{\#Clicked\ News\ Items\ from\ T\ Ranked\ Recommended\ List}{T} \quad \rightarrow (13)$$

Here T indicates the top-ranked news articles based on the user interest and this value may be changed based on the user request. In the evaluation part, precision values are calculated by varying the T values.

$$nDCG_{U_k}(f) = \sum_{l=1}^{n} C_T^f . D(T) \quad \rightarrow (14)$$

Here, T indicates the number of top-ranking news articles and n is the total number of articles recommended by the proposed method. The C_T R indicates the clicking factor and $D(T)$ is a discount factor. The discount factor $D(T)$ has been calculated by using the equation (15),

$$D(T) = \frac{1}{\log(1+T)} \quad \rightarrow (15)$$

The following news recommendation methods are considered for the performance evaluation and these methods are more suitable and related to the proposed methods, Zheng et al. [40], François Chollet et al. [45], Steffen Rendle [46], Cheng [47], Li [30] and Wang et al. [48]. Zheng et al [40] method uses the deep Q learning method, François Chollet et al. [45] uses the logistic regression method, Steffen Rendle [46] uses the factorization method, Cheng [47] uses wide and deep learning method, Li [30] uses linear upper confidence bound method and Wang et al. [48] uses the hidden linear upper bound method. The experiment evaluation uses the same news recommended list generated based on sensitive scores and reward points [30][40][48] and probability values based on click [45][46][47]. Table 1 illustrates the evaluation result by using the dataset of MIND [41]assuming the value of T as 5. Table 1 is generated with the news recommendation of 20 instances

News Recommendation Methods	CTR	P	nDCG
Zheng et al. [40]	0.1123	0.2316	0.9124
François Chollet et al. [45]	0.0164	0.0231	0.2351
Steffen Rendle [46]	0.0472	0.0314	0.3162
Cheng [47]	0.0632	0.0391	0.3953
Li [30]	0.0682	0.0416	0.4672
Wang et al. [48]	0.0736	0.0512	0.5149
Proposed Method	0.1906	0.3156	1.0182

Table 1: Accuracy with 20 recommended News Instances

Table 2 illustrates the evaluation result by assuming the T value as 10 and the news recommendation as 40 instances

News Recommendation Methods	CTR	P	nDCG
Zheng et al. [40]	0.4371	0.4624	1.5478
François Chollet et al. [45]	0.0247	0.0514	0.8521
Steffen Rendle [46]	0.0523	0.0624	0.9231
Cheng [47]	0.0724	0.0627	0.9032
Li [30]	0.0775	0.0763	1.0243
Wang et al. [48]	0.0845	0.0837	1.1956
Proposed Method	0.6063	0.7672	1.8927

Table 2: Accuracy with 40 recommended News Instances

The effectiveness of the exploration has been evaluated by the diversity of news recommendations with existing recommendation methods [1][49]. The equation (16) is used to calculate the diversity in the news recommendation methods.

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$$ILS_{SRNList} = \frac{\sum_{x_i \in SRNList} \sum_{x_j \in SRNList, x_j \neq x_i} S(x_i, x_j)}{\sum_{x_i \in SRNList} \sum_{x_j \in SRNList, x_j \neq x_i} 1} \rightarrow (16)$$

Here $S(x_i, x_j)$ indicate the similarity measures between two news instances from the recommended news lists $SRNList$. The similarity between news recommended lists is measured based on cosine similarity with bag-of-words vectors of news. The proposed method introducing the weight factors is an additional factor to introduce dynamic news recommendations. This weight value will add diversity in the news recommendations and this will avoid the local and global optima problem in the news recommendation system. Table 3 illustrates the diversity of news clicked events with the existing MIND dataset. The total number of news instances considered for this evaluation is 60 news instances and refreshing rates are 15, 20, and 25 news per minute.

News Recommendation Methods	ILS_{15}	ILS_{20}	ILS_{25}
Zheng et al. [40]	0.2731	0.2212	0.2096
François Chollet et al. [45]	0.1457	0.1172	0.1095
Steffen Rendle [46]	0.2761	0.2319	0.2134
Cheng [47]	0.2493	0.2204	0.2037
Li [30]	0.3312	0.3127	0.2956
Wang et al. [48]	0.3176	0.2954	0.2732
Proposed Method	0.3345	0.3257	0.3077

Table 3: Accuracy based on News Diversity with different refreshing rate

CONCLUSION

The paper proposed a news recommendation system using a reinforcement learning technique with agent design based on the ABC optimization algorithm. The proposed recommendation system prepares enriched news articles as recommended news lists by using the ABC optimization algorithm. The user interest list will be updated based on the news click done by the particular user and this will introduce freshness in the news recommendation system. The environment will return a high reward point based on the sentiment score in addition to the weight factor. The newsreader interest list will be created based on the number of clicks and the number of keyword matches. The performance evaluation for the proposed method has been measured based on Click Through Rate (CTR). The proposed method achieves a high CTR rate(0.6063)compared to the other news recommendation systems. The accuracy of the proposed method was measured through the diversity of news clicks and the proposed method achieves maximum diversity (0.3345) value compared to other news recommendation systems

REFRENCES

[1] Cai-Nicolas Ziegler, Sean M McNee, Joseph A Konstan, and Georg Lausen. 2005. Improving recommendation lists through topic diversification. In *Proceedings of the 14th International Conference on World Wide Web*. ACM, 22–32
[2] Shumpei Okura, Yukihiro Tagami, Shingo Ono, and Akira Tajima. 2017. Embedding-based news recommendation for millions of users. In KDD. 1933–1942
[3] Chuhan Wu, Fangzhao Wu, MingxiaoAn, Jianqiang Huang, Yongfeng Huang, and Xing Xie. 2019. Npa: Neural news recommendation with personalized attention. In KDD. 2576–2584
[4] Miaomiao Li and Licheng Wang. 2019. A Survey on Personalized News Recommendation Technology. IEEE Access 7 (2019), 145861–145879
[5] Chuhan Wu, Fangzhao Wu, MingxiaoAn, Jianqiang Huang, Yongfeng Huang, and Xing Xie. 2019. Neural news recommendation with attentive multi-view learning. In IJCAI. AAAI Press, 3863–3869
[6] hong Feng, Muzammil Khan, Arif Ur Rahman, and Arshad Ahmad. 2020. News Recommendation SystemsAccomplishments, Challenges & Future Directions. IEEE Access 8 (2020), 16702–16725
[7] ToineBogers and Antal Van den Bosch. 2007. Comparing and evaluating information retrieval algorithms for news recommendation. In Recsys. 141–144

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
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[8] Hugo L Borges and Ana C Lorena. 2010. A survey on recommender systems for news data. In Smart Information and Knowledge Management. Springer, 129–151
[9] DoychinDoychev, Aonghus Lawlor, Rachael Rafter, and Barry Smyth. 2014. An analysis of recommender algorithms for online news. In CLEF. 177–184.
[10] M Durairaj and K Muthu Kumar. 2014. News recommendation systems using web mining: a study. In International Journal of Engineering Trends and Technology, Vol. 126. 293–299.
[11] Sanjay K Dwivedi and Chandrakala Arya. 2016. A survey of news recommendation approaches. In ICTBIG. IEEE, 1–6
[12] Chong Feng, Muzammil Khan, Arif Ur Rahman, and Arshad Ahmad. 2020. News Recommendation SystemsAccomplishments, Challenges & Future Directions. IEEE Access 8 (2020), 16702–16725.
[13] MahboobehHarandi and Jon AtleGulla. 2015. Survey of User Profiling in News Recommender Systems. In INRA@ECML PKDD. 20–26
[14] MozhganKarimi, DietmarJannach, and Michael Jugovac. 2018. News recommender systems–Survey and roads ahead. Information Processing & Management 54, 6 (2018), 1203–1227
[15] Lei Li, Ding-Ding Wang, Shun-Zhi Zhu, and Tao Li. 2011. Personalized news recommendation: a review and an experimental investigation. Journal of Computer Science and Technology 26, 5 (2011), 754
[16] ÖzlemÖzgöbek, Jon AtleGulla, and RizaCenkErdur. 2014. A Survey on Challenges and Methods in News Recommendation. In WEBIST. 278–285.
[17] Jing Qin. 2020. Research Progress of News Recommendation Methods. arXiv preprint arXiv:2012.02360 (2020)
[18] Mansi Sood and Harmeet Kaur. 2014. Survey on news recommendation. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering 3, 6 (2014), 9972–9977
[19] Shumpei Okura, Yukihiro Tagami, Shingo Ono, and Akira Tajima. 2017. Embedding-based news recommendation for millions of users. In KDD. 1933–1942
[20] Victor Lavrenko, Matt Schmill, Dawn Lawrie, Paul Ogilvie, David Jensen, and James Allan. 2000. Language models for financial news recommendation. In CIKM. 389–396
[21] F Corsini and MA Larson. 2016. CLEF NewsREEL 2016: Image based Recommendation. In CLEF. 593–605
[22] Andreas Lommatzsch, Benjamin Kille, Frank Hopfgartner, and Leif Ramming. 2018. NewsREEL Multimedia at MediaEval 2018: News Recommendation with Image and Text Content. In MediaEval. CEUR-WS
[23] Cornelius A Ludmann. 2017. Recommending News Articles in the CLEF News Recommendation Evaluation Lab with the Data Stream Management System Odysseus.. In CLEF
[24] JungAe Yang. 2016. Effects of popularity-based news recommendations ("most-viewed") on users' exposure to online news. Media Psychology 19, 2 (2016), 243–271
[25] Xuejian Wang, Lantao Yu, Kan Ren, Guanyu Tao, Weinan Zhang, Yong Yu, and Jun Wang. 2017. Dynamic attention deep model for article recommendation by learning human editors' demonstration. In KDD. 2051–2059
[26] Cheng Chen, XiangwuMeng, Zhenghua Xu, and Thomas Lukasiewicz. 2017. Location-aware personalized news recommendation with deep semantic analysis. IEEE Access 5 (2017), 1624–1638
[27] Jeong-Woo Son, A-Yeong Kim, and Seong-Bae Park. 2013. A location-based news article recommendation with explicit localized semantic analysis. In SIGIR. 293–302
[28] WouterIJntema, Frank Goossen, Flavius Frasincar, and Frederik Hogenboom. 2010. "Ontology-based news recommendation," In *Proceedings of the 2010 EDBT/ICDT Workshops*. ACM, 16, pp. 1-6, https://doi.org/10.1145/1754239.1754257
[29] Michal Kompan and MáriaBieliková. 2010. Content-Based News Recommendation.. In *EC-Web*, Vol. 61. Springer, pp. 61–72
[30] Lihong Li, Wei Chu, John Langford, and Robert E Schapire. 2010. A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th international conference on World wide web*. ACM, pp. 661–670
[31] Lei Li, Dingding Wang, Tao Li, Daniel Knox, and BalajiPadmanabhan. 2011. SCENE: a scalable two-stage personalized news recommendation system. In *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*. ACM, 125–134

Journal of Information Systems Engineering and Management
2025, 10(56s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

[32] Jiahui Liu, Peter Dolan, and Elin Rønby Pedersen. 2010. Personalized news recommendation based on click behavior. In *Proceedings of the 15th international conference on Intelligent user interfaces* . ACM, 31–40
[33] Zhongqi Lu and Qiang Yang. 2016. Partially Observable Markov Decision Process for Recommender Systems. *arXiv preprint arXiv:1608.07793* (2016)
[34] Xiangyu Zhao et al., "Deep reinforcement learning for page-wise recommendations", *Proceedings of the 12th ACM Conference on Recommender Systems*, 2018, pp. 95-103, https://doi.org/10.1145/3240323.3240374
[35] Lixin Zou et al., "Reinforcement learning to optimize long-term user engagement in recommender systems", *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2019
[36] SaravanapriyaManoharan and RadhaSenthilkumar, "An Intelligent Fuzzy Rule-Based Personalized News Recommendation Using Social Media Mining", *Computational Intelligence and Neuroscience*, vol. 2020, pp. 10, 2020, [online] Available: https://doi.org/10.1155/2020/3791541
[37] S. Bangari, S. Nayak, L. Patel and K. T. Rashmi, "A Review on Reinforcement Learning based News Recommendation Systems and its challenges," *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, Coimbatore, India, 2021, pp. 260-265, doi: 10.1109/ICAIS50930.2021.9395812\
[38] A. Kabra and A. Agarwal, "Personalized and Dynamic top-k Recommendation System using Context Aware Deep Reinforcement Learning," *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, Madrid, Spain, 2021, pp. 238-247, doi: 10.1109/COMPSAC51774.2021.00042
[39] Z. Song, D. Zhang, X. Shi, W. Li, C. Ma and L. Wu, "DEN-DQL: Quick Convergent Deep Q-Learning with Double Exploration Networks for News Recommendation," *2021 International Joint Conference on Neural Networks (IJCNN)*, Shenzhen, China, 2021, pp. 1-8, doi: 10.1109/IJCNN52387.2021.9533818
[40] Guanjie Zheng, Fuzheng Zhang, Zihan Zheng, Yang Xiang Nicholas Jing Yuan, Xing Xie, and Zhenhui Li. 2018., "DRN: A Deep Reinforcement Learning Framework for News Recommendation," In *WWW 2018: The 2018 Web Conference, April 23–27, 2018, Lyon, France. ACM, New York, NY, USA*. https://doi.org/10.1145/3178876.3185994\
[41] Fangzhao Wu, Ying Qiao, Jiun-Hung Chen, Chuhan Wu, Tao Qi, JianxunLian, Danyang Liu, Xing Xie, Jianfeng Gao, Winnie Wu, and Ming Zhou, "MIND: A Large-scale Dataset for News Recommendation," In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3597–3606, 2020
[42] Karaboga, D., Basturk, B. A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. *J Glob Optim* **39**, 459–471 (2007). https://doi.org/10.1007/s10898-007-9149-x
[43] Tereshko, V., Loengarov, A. (2005), Collective decision-making in honey bee foraging dynamics, Computing and Information Systems, 9 (3): 1-7, University of the West of Scotland, UK
[44] Yining Wang, Liwei Wang, Yuanzhi Li, Di He, and Tie-Yan Liu, "A theoretical analysis of ndcg type ranking measures," In *Conference on Learning Theory* . pp. 25–54, 2013
[45] François Chollet *et al.* 2015. Keras. https://github.com/fchollet/keras. (2015)
[46] Steffen Rendle. 2010. Factorization machines. In *Data Mining (ICDM), 2010 IEEE 10th International Conference on* . IEEE, 995–1000
[47] Heng-Tze Cheng, LeventKoc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, HrishiAradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, *et al.* 2016. Wide & deep learning for recommender systems. In *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems* . ACM, 7–10
[48] Huazheng Wang, Qingyun Wu, and Hongning Wang. 2016. Learning Hidden Features for Contextual Bandits. In *Proceedings of the 25th ACM International on Conference on Information and Knowledge Management* . ACM, 1633–1642
[49] GediminasAdomavicius and YoungOk Kwon. 2012. Improving aggregate recommendation diversity using ranking-based techniques. *IEEE Transactions on Knowledge and Data Engineering* 24, 5(2012), 896–911