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Research Article

Deep Inverse Reinforcement Learning for Adaptive 6G Network Optimization and Disaster Response in Smart Cities

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Abstract – *It is anticipated that the quick development of 6G mobile communication networks will revolutionise smart cities by making intelligent transportation, healthcare, manufacturing, and residential services possible. Resilient 6G Network Optimisation is necessary to guarantee the continuous operation of vital services in the event of technological malfunctions, human mistake, natural disasters, or terrorist attacks, as societies become more reliant on digital infrastructure. The suggested MaximumEnt-InverseRL system uses a thorough data processing pipeline that includes feature engineering, categorical encoding, feature scaling, outlier detection and removal, and managing missing values in order to overcome this difficulty. To enhance prediction performance, a hybrid feature selection approach that combines ensemble learning and CFS-RF is used. Additionally, to facilitate intelligent network decision-making, the Maximum Entropy Principle (MEP) is combined with Reinforcement Learning (RL) and a Deep Neural Network (DNN)-based reward function within an Inverse Reinforcement Learning (IRL) framework. The suggested MaximumEnt-InverseRL model, which achieves an exceptional accuracy of 95.03%, greatly improves 6G Network Optimisation while enhancing Disaster Response in Smart Cities, according to simulation findings. These results show that the suggested strategy provides a strong and flexible way to preserve resilient 6G infrastructure and guarantee the continuation of vital urban services in the event of unexpected disruptions.*

Keywords— *Radio Frequency Identification (RFID), Emergency Medical Service (EMS), Inverse Reinforcement Learning (IRL), Correlation-based Feature Selection and Random Forest (CFS-RF).*

I. INTRODUCTION

Natural Disasters such as hurricanes, earthquakes, and floods cause immense devastation every year, killing countless numbers of people and injuring hundreds of thousands more [1]. Damage to buildings, power plants, water treatment facilities, and bridges, among other infrastructure, causes thousands of people to become homeless and costs affected nations millions if not billions of dollars in lost revenue [2]. There are two main types of emergency localisation systems: passive and active. Passive systems require the user device to continually transmit its position data and wait for assistance to be requested. On the other hand, active systems require the user device to actively begin assistance requests. Indoor positioning systems

enhanced with smart sensors can be of assistance in this matter by transmitting the current position of the occupants to a secure server, allowing first responders to locate them and directing them to the safest area within the building.

In order to accurately locate devices within smart buildings, it is possible to include efficient tools such as GPS, WiFi, Zigbee, camera-based visualisation, and RFID technology [3]. Furthermore, for effortless health monitoring, wireless medicinal body sensors can continually upload vital signs. From a rescuer's point of view, including sensors into footwear, clothing, and helmets can greatly enhance safety and help authorities find people at disaster sites. Disasters like hurricanes, floods, and earthquakes that have occurred recently prove that current mobile communication technologies aren't prepared to withstand extreme conditions [4]. In times of critical communication, this poses substantial problems for society. Similar complexity is anticipated in the architecture of the next-generation communication system. Given the ever-changing nature of network conditions caused by factors such as mobility, failures, and unusual spikes in network traffic, the resources allocated to 6G network slices must be adjusted quickly and autonomously.

Here is how the rest of the paper is structured: Following a brief overview of relevant literature on 6G network optimisation and smart city disaster response in Section 2, the paper introduces the MaximumEnt-InverseRL model in Section 3, describes the experimental setup and results in Section 4 and ends with suggestions for future research in Section 5.

II. RELATED WORKS

As both natural and man-made disasters are becoming increasingly commonplace on a worldwide scale, the need for well-thought-out plans to respond to emergencies has grown. The protection of life, property, and essential services must be ensured in the event of a pandemic, hurricane, wildfire, or other urban infrastructure disaster by swift and coordinated responses[5]. Critical areas of study would thus include real-time disaster management using fog computing and AI. These advantages could be realized by deploying extremely lightweight AI models that can use quantised CNNs and LSTM directly on fog nodes [6]. These nodes would analyse sensor data in real time, allowing for localised responses, rather than relying on the slower centralised cloud infrastructure [7]. The results of recent experiments show that this approach has been quite successful, outperforming conventional systems in terms of latency reduction and prediction accuracy. For example, flood prediction systems have demonstrated that relying solely on cloud AI models will postpone alerts, whereas edge computing allows for decision-making in near real-time [8]. Their ANN model outperformed the status quo by employing numerous hidden layers rather of a single one, leading to significantly improved accuracy [10]. They successfully achieved an overall classification accuracy using their proposed flood plain mapping method by using SVM to split the cloud, land, and water sectors from satellite information [9].

A popular technique for energy load profile clustering, the K-means clustering algorithm allows for weekend, weekday, and holiday grouping, and is particularly useful for residential load profiles [11]. There is a lack of research on how to distinguish between typical and unusual load profiles as a result of natural catastrophes in the literature on load profile clustering. Using the K-means clustering technique, this work seeks to detect clusters that occur before and after natural disasters, as well as to capture the traits of these types of events. The discovery that DQN could perform as well as humans on control tasks was a

huge step forward in RL study. Due to this development, RL can now be used in real-world systems where non-linearity and uncertainty make classic optimisation methods fail. One use of RL in emergency management is the capacity to optimise dispatch decisions and resource allocation in response to dynamic environmental conditions [12]. In order to solve cluster routing problems optimally, they detailed a multi-level clustering method that, at each planning level, grouped demand nodes into smaller clusters [13]. By grouping EMS needs together in the past, they were able to take the distance between possible sites of short-term EMS facilities into account. In addition, several EMS facility location models rely on heuristic techniques. A GA was developed and evaluated on two benchmark datasets. The results that were produced by GA were marginally superior than those that were produced using a Lagrangian heuristic and a substitution process. 6G network optimisation and disaster response in smart cities are two problems that they aim to address with three novel MaximumEnt-InverseRL algorithms. 6G network optimisation and disaster response in smart cities cannot be solved by the variants of MaximumEnt-InverseRL algorithms that have been developed by various academics. Our approach differs from recent MaximumEnt-InverseRL formulations in that it utilises a deep neural network to approximatively calculate the state-action reward rather than the state reward.

III. METHODLOGY

Telecom infrastructures are facing significant challenges in keeping up with the rapid expansion of smart cities. These infrastructures need to be able to handle bursty traffic loads and diverse service needs with ease and scalability. The ever-evolving demands of smart city environments, including driverless automobiles, the IoT and public safety systems, are too much for legacy network systems to manage. The specific problems faced by smart cities and the technical developments that enhance network functionality have recently received more and more focus with the introduction of 6G networks. To tackle the inherent complexity of next-generation telecommunications networks, network slicing has been proposed as a potential solution.

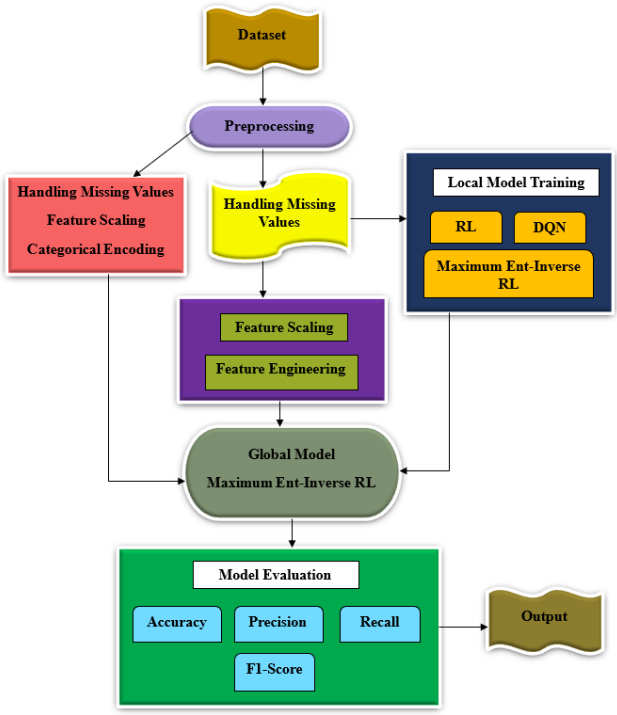


Fig. 1. The Flowchart for Proposed Model

The research framework shows the whole procedure for developing the MaximumEnt-InverseRL model. This privacy-preserving decentralised training is implemented throughout smart cities as shown in Fig.1, which depicts the workflow from data preprocessing, feature selection, MaximumEnt-InverseRL model training and evaluation.

A. Dataset Description

Built for studies on dynamic resource optimisation and allocation, this dataset depicts

the state of communication networks[14]. It records a wide range of data from different situations, including network conditions, user demand, resource availability and performance outcomes.

Key Features

User load, channel quality, traffic demand, power, signal strength, and edge computing capacity are all elements that make up comprehensive state variables.

Included in the Action Space for Resource Management are decisions on unloading, routing, power control, and channel assignment.

This scalable dataset includes 1500 samples and can be easily expanded or contracted as needed.

B. Data PreProcessing

Prior to training the MaximumEnt-InverseRL model, the dataset underwent thorough preprocessing to increase data consistency and quality and to prepare it for deep learning and federated learning tasks. The following main procedures were used to complete these steps:

1) HandlingMissingValues

It used linear interpolation to fill in the small gaps in the 6G Network observations such that the data remained consistent over time and not skewed significantly.

2) Feature Scaling

Equation (1) makes use of Min-Max scaling, which normalises values between 0 and 1.

$$W' = \frac{W - W_{min}}{W_{max} - W_{min}} \quad (1)$$

3) Categorical Encoding

The Junction' attribute was subjected to one hot encoding in order to generate binary indications while maintaining the spatial information's non-ordinality.

4) Outlier Detection and Removal

It capped extreme outliers at the 99th percentile to lessen their impact without deleting informative observations.

5) Feature Engineering

To facilitate pattern learning in cyclical urban behaviour, additional temporal characteristics including hour, day and month were obtained from the timestamp.

Linear interpolation was used to manage the uniformly distributed missing values in the vehicle's column, ensuring that the data remained consistent throughout time. To prevent the removal of useful records due to outliers, data points were capped after reaching the 99th percentile. This capped the extreme values[15]. In order to standardise the input distributions between 0 and 1, they utilised Min-Max scaling across all numerical features. To remove any potential bias in the model's spatial learning caused by the assumption of ordinal relationships across places, the categorical nature of the junction IDs was preserved by one-hot encoding.

C. Feature Selection

A hybrid technique for effective FS and accurate categorisation was established by combining CFS with bagging EL[16]. The system makes use of the reimplemented hybrid CFS-RF for FS, as seen in Algorithm 1.

Algorithm 1: Algorithm for CFS-RF hybrid technique
Input: Classes of features e_1, e_2, e_3 & e_4
Output: Estimated accuracy and final assessment

Begin
1. Loop
2. For each merit of CFS generate a subset of random Forest Randomly.
3. Make a distinction between the most pertinent
4. and irrelevant features
5. For each subset
6. Compute ω_j & σ^2
7. End For
8. Dimensionality reduction and the identification of the most pertinent aspects
9. If the discretisation of the datasets do
10. evaluation and estimated accuracy
11. End if
12. End For
13. Return Features classes
End

Here is an outline of the hybrid CFS-RF approach that was reimplemented: Equation (2) shows how it applies the W_j value obtained from preprocessing to each feature using the merit equation.

$$= \frac{\rho_t}{\overline{dq_l e}} \Big/ \sqrt{d + d(d-1) + \overline{q_e e}} \qquad (2)$$

where $\overline{q_e e}$is the correlation between features and classes and $\overline{q_l e}$ is the correlation between features and other classes. The computed correlation (CFS) clarifies Equation. Then, it uses equation (3) to generate RF subsets.

$$\{g(d, w, \theta_d = 1,2,3, \dots)\} \qquad (3)$$

The variables l, d, g & w stand for integers, theta, frequency and vectors, respectively. Equation (4) confirms the redundant characteristics by computing the weight range.

$$\omega Q^{\lambda} = \begin{cases} \left[0.000, \binom{-1}{f^{-\lambda}}\right], \lambda = 1 \\ \left[\binom{-1}{f^{\lambda-1}} + o, f^{\binom{-1}{\lambda}}\right], \lambda > 1 \end{cases} \qquad (4)$$

where ωQ^{λ} stands for the weight range and λ for the lambda. The most relevant feature with the lowest standard deviation is found by dividing by equation (5), the standard deviation, to get the value of σ_j.

$$\sigma_j = \frac{1.0 - \omega_j}{(m+1) - \lambda} \qquad (5)$$

where ω_j stands for weight and σ_j for standard division.

Model Training

MaxEnt Deep IRL Algorithm

Using the maximum entropy principle as a foundation, they provide a concise overview of the IRL technique that was employed to learn the unknown parameters of the DNN. Let begin by going over the model learning process, since it is necessary to know it in order to calculate the predicted state-action visitation number.

Model Learning

When there is no information regarding the state transition model $o(t'/t, b)$, there is a scenario that is entirely devoid of models[17]. Equation (6) gives the likelihood of each conceivable outcome of the state transitions; this allows one to analyse the visitation count of each state-action-state triple, which is the basis of model learning.

$$o(t'/t, b) = \frac{u(t, b, t')}{\sum_{t' \epsilon T} u(t, b, t')} \qquad (6)$$

When the sum of all transitions from state t to state t' caused by action an is denoted as

$u(t,b,t')$. As the count of state visits $u(t,b,t')$ approaches infinity, the probability $o(t'/t,b)$begins to approach its true value. Consider combining Q-learning with model learning.

IRL Algorithm

In order to achieve this goal, let will first provide the algorithm that will be used to generate the model learning result $o(t'/t,b)$and then use it to compute the expected state-action visitation counts $F[\rho(t,b)]$.

The terminal or target state, T_{final}., is where the system's state will not change; no future state transitions can occur at T_{final}. The next step is to update the DNN's parameters θ using gradient ascent, after which the gradient $\frac{\partial K_C}{\partial \theta}$ is calculated using equation (7). The value of $\Delta\theta$ can be determined by using equation.

$$\Delta\theta = \lambda \frac{\partial K_C}{\partial \theta} \quad (7)$$

where the learning rate is denoted as λ (time step). Another option is to incorporate a weight decay term into AE as a model regularizer, comparable to an K_2 regularizer or a K_1 regularizer, among others. Regularizers can be employed to convexify the problem, reduce the likelihood of overfitting or add qualities like monotonicity to the optimisation problem, for example by incorporating a self-defined cost term.

IRL Algorithm Refinement

When learning the model, it's important to visit each state-action pair many times before expecting good results. When the state transition probability $o\left(\frac{t'}{t},b\right)$ is incorrect, it can cause problems with $\partial K^C/\partial Q(t,b)$, which in turn cause problems with the gradients $\partial K^C/\partial\theta$which are used to update the neural network parameters θ. This problem can be solved by pre-learning the model until it converges, and then using it. However, when the system is complex and the behaviour of the stochastic system over time needs to be represented, the demonstrations in may fall short in accurately portraying the environment's random behaviour. To prevent making a huge mistake when projecting the system's long-term behaviour, one can either break the demonstrations into smaller parts or attempt not to use the state transition terms when calculating the gradients.

Using the original demonstrations, it regenerates several new sets of mathematical $C_\varsigma\epsilon\{\zeta_\varsigma^j, j=1,\dots,M_\varsigma\}$results in this work. All of the following requirements are met by the elementζ_ς^j: 1) ζ_ς^j begins at the state specified by $\varsigma\epsilon T$, 2) For all $\varsigma\epsilon T$, the length of ζ_ς^j remains constant ΔS. Thirdly, $\zeta \in C$ can be reached by a path $\zeta_\varsigma^j \subseteq \zeta$. The path space that corresponds ζ_ς^j to it is represented as Ω_ς. Under the limitations imposed by the C_ς demonstrations in equations (8), it proceeds to maximise the entropy $\Omega_\varsigma$of the combined distribution over both variables.

$$\theta^* = arg\max_\theta K_C(\theta)$$

$$\theta^* = arg\max_\theta \sum_{\varsigma\epsilon T}\left(\frac{1}{M_\varsigma}\left(\sum_{\zeta\epsilon C_\varsigma}\left(\sum_{(t,b)\epsilon\zeta} Q(\theta;t,b) + \sum_{(t,b,t')\epsilon\zeta} o(t'/t,b)\right)\right) - logY_\varsigma(\theta)\right) \quad (8)$$

where equation (9) gives the partition function Y_ς.

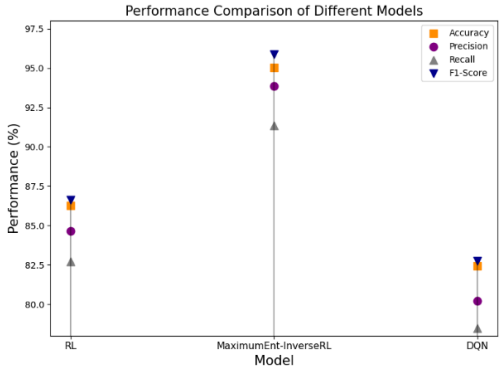
$$Y_\varsigma(\theta) = \sum_{\zeta\epsilon\Omega_\varsigma} f^{\Sigma_{(t,b)\epsilon\zeta} Q(\theta;t,b)} \quad (9)$$

Equation (10) provides the partial derivative of K_C with regard to the partial derivative of θ.

$$\frac{\partial K_C(\theta)}{\partial \theta} = \sum_{t \epsilon T} \sum_{b \epsilon B} \frac{\partial K_C(\theta)}{\partial Q(\theta; t, b)} \frac{\partial Q(\theta; t, b)}{\partial \theta} \quad (10)$$

IV. RESULT AND DISCUSSION

Natural disasters are becoming more frequent as a result of human activity's rapid contribution to climate change and the acceleration of deforestation. This has significant impact on the environment and has increased the urgency of the need for disaster-resilient urban planning. This study intends to critically examine many advanced technologies, such as the adoption of sixth generation communication networks, in order to fill the gaps left by previous research that has solely focused on disaster prediction.



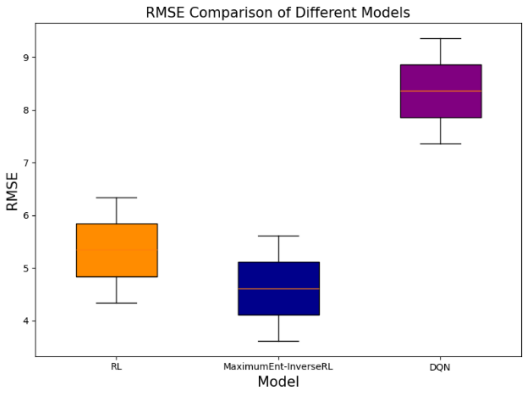
Performance Comparison of Different Models

The recall, accuracy, precision and F1score of several models including RL, MaximumEnt-InverseRL, and DQN are compared in Fig. 2. In comparison to the other two models, the proposed MaximumEnt-InverseRL strategy performs well, achieving F1-Score of 95.69%, accuracy of 95.03%, precision of 93.86% and recall of 91.36%.

Performance Comparison

Model	Acc	Pre	Recl	F1-Score
RL	86.28	84.64	82.73	86.64
MaximumEnt-InverseRL	95.03	93.86	91.36	95.89
DQN	82.41	80.21	78.47	82.76

A comparison of the recall, accuracy, precision and f1score for different models, including RL, MaximumEnt-InverseRL and DQN, is shown in Table 1. With a F1-Score of 95.69%, accuracy of 95.03%, precision of 93.86% and recall of 91.36%, the MaximumEnt-InverseRL method outperforms the other two models.



RMSE Comparison of Different Models

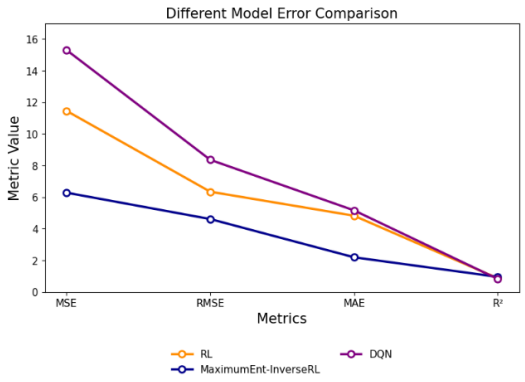
Higher prediction accuracy is indicated by the lower RMSE values produced by models MaximumEnt-InverseRL. DQN and RL have extremely high RMSE values, whereas MaximumEnt-InverseRL has the lowest median RMSE (Fig. 3). In comparison to the other models, DQN's greater value range and highest RMSE signify a more substantial prediction error and variability.

Error Comparative analysis

Model	MSE	RMSE	MAE	R2

RL	11.46	6.34	4.82	0.86
MaximumEnt-InverseRL	6.28	4.61	2.19	0.95
DQN	15.31	8.36	5.16	0.82

Table 2 shows a comparison of three prediction models across four important assessment metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R2). The models included RL, DQN and the suggested MaximumEnt-InverseRL model. Reaching the lowest MSE (6.28), RMSE (4.61), and MAE (2.19), while earning the greatest R2 value of 0.95, demonstrating good correlation between projected and real traffic counts, the MaximumEnt-InverseRL model outperforms all other models.



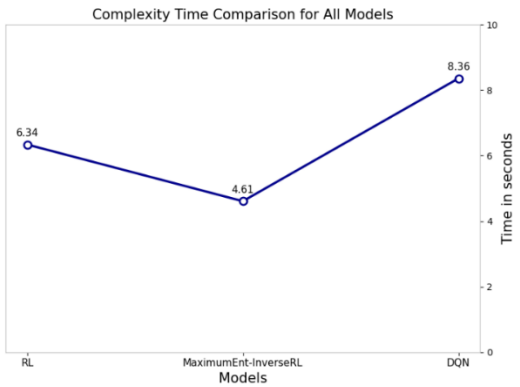
Different Model Error Comparison

Three prediction models are compared in Fig. 4 using four key evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R2). The models included the proposed MaximumEnt-InverseRL model, RL and DQN. The MaximumEnt-InverseRL model outperforms all other models with the lowest MSE (6.28), RMSE (4.61), and MAE (2.19), as well as the highest R2 value of 0.95, indicating a strong correlation between projected and actual traffic counts.

Disaster Comparison for Different Model

Disaster Type	Acc	Precl	Recl	F1-Score
Floods	95.03	93.86	91.36	95.89
Fire	82.41	80.21	78.47	82.76
Earthquakes	86.28	84.64	82.73	86.64
Evacuation Routing	90.24	88.36	86.21	90.91

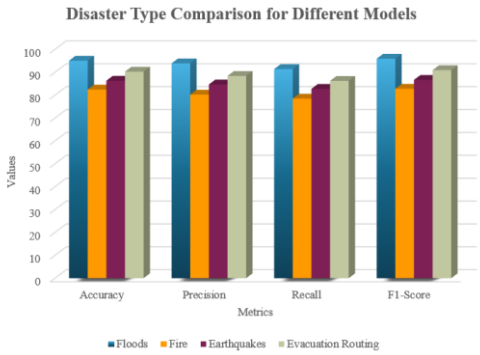
Table 3 shows a disaster comparison for four disaster types Floods, Fire, Earthquakes and Evacuation Routing utilising Accuracy, Precision, Recall and F1-Score metrics. Floods had the best overall performance with 95.03% accuracy, 93.86% precision, 91.36% recall and 95.89% F1-score. Fire exhibits the lowest performance across all metrics.



Complexity Time Comparison for All Models

Fig.5 shows the maximum and minimum values of the complexity time comparison for all models. DQN, MaximumEnt-InverseRL and RL were employed to characterise the execution

time. The minimum time for the MaximumEnt-InverseRL model was 4.61 seconds, whereas DQN model reached a maximum of 8.36 seconds.



Disaster Type Comparison for Different Models

Fig. 6 shows that several models have made great progress in comparing disaster types. A new method of flood prediction was developed that successfully captured patterns in river-level data over time, resulting in an F1-score of 95.69%. False alarms decreased by 15% compared to the conventional threshold approaches used for fire detection. In simulated metropolitan contexts, evacuation routing agents were also 22% faster than algorithm in selecting pathways.

V. CONCLUSION

The advancement of 6G and smart city innovations is anticipated to revolutionise urban life by facilitating intelligent healthcare, transportation, manufacturing, and IoT-based public services. Future wireless communication systems, building on the 5G foundation, need resilient 6G Network Optimisation to provide dependable connectivity while tackling issues like data privacy, security, interoperability, digital inclusion, and large-scale adoption. In order to accomplish this, the suggested MaximumEnt-InverseRL framework uses a thorough data preparation procedure that includes feature engineering, category encoding, feature scaling, handling missing values, and outlier detection and removal. To enhance model performance, a hybrid feature selection strategy combining ensemble learning and CFS-RF is then applied. Additionally, using continuously differentiable parameterised function approximators to Maximum Entropy Inverse Reinforcement Learning, the study makes it possible to learn effectively even with a limited understanding of stochastic network behaviour. Through intelligent and adaptable network management, simulation findings show that the combination of Reinforcement Learning and Inverse Reinforcement Learning greatly improves 6G Network Optimisation while enhancing Disaster Response in Smart Cities. The suggested MaximumEnt-InverseRL model attains an exceptional accuracy of 95.03% showcasing its efficacy in preserving robust communication systems and maintaining essential urban services among unexpected disruptions.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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