# Addressing Climate Change and Port Emissions : An In-Depth Analysis and Optimization of Maritime Trajectory Reconstruction using Hybrid AI Methodologies

Boutheina Jlifi[1,2,3*], Senda Sellami[1*], Claude Duvallet[2], Khaled Guesmi[3], Marc-Arthur Diaye[4]

*Abstract*— **The maritime transportation sector is as important as air and land transportation and must operate sustainability, minimizing waste and negative environmental impact. The optimization of vessel trajectories can achieve decarbonization and sustainability in this sector. This research supports climate finance goals by using data and information to make better decisions that reduce pollution and promote an environmentally friendly approach that improves shipping efficiency. In this methodological study, we review current research on vessel trajectory reconstruction, analyzing their strengths and limitations. We propose a novel approach that combines these current methods with advanced Artificial Intelligence (AI) techniques for better accuracy and efficiency in trajectory reconstruction. It is composed of four main steps; First, denoising the Automatic Identification System (AIS) data using Geohash-based Dynamic Time Warping (DTW) then applying U-Net for refining the trajectory grid. Second, extracting the most relevant trajectory features using Ant Colony Optimization (ACO). Third, reconstructing the trajectory using Geohash-DTW for long gaps and kinematic interpolation for short gaps. Finally, applying a temporal refinement using Bidirectional Gated Recurrent Unit (BiGRU) and optimizing the hyperparameters by applying a Genetic Algorithm (GA).**

**Keywords : Trajectory reconstruction, maritime transportation, decarbonization, AI techniques, computational intelligence, energy transition, climate change, AIS data, Dynamic Time Warping (DTW).**

## I. INTRODUCTION

### A. Motivations and Challenges

Maritime transportation is the backbone of world trade: As much as up to 90% of the goods traded globally are transported by sea [1]. It is important for global trade and sustainability, with efforts to reduce carbon emissions we can achieve decarbonization and more efficient navigation. Some authors suggested ideas for decarbonization vessels; [2] proposed adding solar panels on ships to reduce the use of fossil fuels and [3] claimed that applying energy rules to fishing boats can improve decarbonization especially when equipping them in the same way as cargo ships, as a result, the oceans will be cleaner. The Automatic Identification System (AIS) provides vessel trajectory data but often suffers from noise [4]. This unclean data can highly affect the Estimated Time of Arrival (ETA) predictions. Strong trajectory reconstruction is important to restoring missing data, improving ETA accuracy and enabling energy-efficient operations for better maritime performance. Despite advancements in trajectory reconstruction, current methods including **Geohash-DTW** [4], **U-Net** [5], **kinematic interpolation** [6] and **BiGRU** [7] face some limitations: they are not efficient at complex navigations and they lack real-time flexibility. Consequently, there is a need for a hybrid solution to solve these problems. New studies in computational intelligence offer successful solutions; according to [8], the use of a genetic algorithm based three hyperparameter optimization of deep long short term memory (**GA3P-DLSTM**) can enhance time series prediction for electric vehicle energy consumption with noise-tolerant predictions. The guided genetic algorithm-based ensemble voting of polynomial regression and lstm (**GGA-PolReg-LSTM)** model [9] uses LSTM and polynomial regression to manage complex data and methods that are also applicable to maritmie trajectory reconstruction. Port operations and infrastructure are being impacted by climate change more and more, which is forcing ports all over the world to make investments in protection and capacity improvement [10]. Climate change also has an effect on trajectory reconstruction because Brandoli et al. [11] discovered changing ocean conditions so new tracking models must be considered. According to [12], unusual weather changes along ship routes still need to be found. All the AI methods and metaheuristics we mentioned in this section, despite their limitations, offer energy-efficient solutions and support climate change reduction and energy transition goals for more accurate trajectory reconstruction and ETA prediction.

### B. Objectives and Contributions

To improve trajectory reconstruction, this work proposes a **hybrid AI-driven framework** combining the methods of existing studies and addressing their limitations. **Key contributions are:**

- **Denoising: Geohash-DTW** detects and remove noisy segments and **U-Net** refines the trajectory grid.
- **Feature Selection: ACO** to extract the most relevant trajectory features.

[1]Ecole Supérieure de Commerce de Tunis (ESCT), SMART Lab ISG, Manouba, Tunisia.
[2]LITIS, Le Havre, Normandie, France.
[3]CRECC – Paris School of Business, Paris, France.
[4]Ecole d'Economie de la Sorbonne, Paris, France.
*Corresponding authors.
E-mail(s):
boutheina.jlifi@esct.uma.tn
senda.sellami@esc.u-manouba.tn
claude.duvallet@univ-lehavre.fr
k.guesmi@psbedu.paris
Marc-Arthur.Diaye@univ-paris1.fr

- **Reconstruction: Geohash-DTW** fills long gaps using ACO-selected features and **Kinematic interpolation** fills short gaps.
- **Temporal Refinement: BiGRU**, improves temporal consistency and **GA** optimizes biGRU and U-Net hyperparameters.

## II. LITERATURE REVIEW

Recent studies in vessel trajectory reconstruction include many methodologies. Liang et al. [4] proposed a hybrid framework combining noise detection, polynomial interpolation and geospatial alignment (Geohash-DTW) for long-term gaps. Guo et al.[6]focused on kinematic refinement, iteratively optimizing acceleration dynamics using harmonic points for high-frequency data.Li et al. [5] presented a U-Net model, converting trajectories into 2D grids to exploit spatial continuity for curved paths and irregular sampling. Chen et al. [7] advanced Machine Learning (ML) approaches with a BiGRU network, classifying trajectories using decision trees and reconstructing gaps using adaptive lasso-weighted motion features. Deep Learning (DL) models like LSTM and CNN improve trajectory prediction but support hybrid solutions, relying on clear AIS data [13]. These existing methods show progress in addressing missing data challenges but each approach has some limitations. A comparative analysis (Table 1) highlights these gaps and underscores the need for a unified method balancing accuracy and efficiency.

TABLE I: Related works of used techniques to reconstruct trajectory

| Used Methodology | Strong Points | Missing Points | Evaluation Metrics | Experiments and Results |
|---|---|---|---|---|
| Trajectory classification (decision tree) + BiGRU for reconstruction [7] | Accurate for ship types; handles speed/turns well; tested widely | Slow processing; errors if ship type misclassified; bad with mixed ships; not real-time; needs labeled data | Root Mean Square Error (RMSE) + Mean Haversine Distance | RMSE as low as 0.007 for small course changes; outperformed baselines in mixed datasets |
| Statistical noise detection + Geaohash-DTW for reconstruction [4] | Fixes long gaps using past paths; smart search tricks | Needs extensive historical data; slow computation | Accuracy (ACC) + Distance Loss (DL) + Mean Absolute Error (MAE) + RMSE + Frechet Distance (FD) + DTW | Tested on 4 datasets (SHP, QZS, TJP, LTC); Achieved higher ACC (99% +) and lower RMSE |
| Iterative anomaly detection + kinematic interpolation (velocity/acceleration modeling) [6] | Uses speed changes; fixes errors step by step | Poor performance for sudden turns; requires frequent data updates | RMSE of Position + RMSE of Speed Over Ground | Lower RMSE (position : 36.3m for KI; SOG : 1.05 knots vs. 1.59 knots) |
| U-Net architecture with skip connections for trajectory grid reconstruction [5] | Good for curves/missing points; clever feature missing | Needs lots of data; struggles with long missing parts | DTW + Structural Similarity Index Measure (SSIM) | Realistic/synthetic datasets; DTW distance : 0.15 vs. 0.197 (cubic spline) for 45% loss rate3 |

The rest of the paper is structured as follows; Section III presents the hybrid methodology with algorithmic design and parameter definitions, section IV presents illustrative example of AIS data and preprocessing and section V covers conclusion and future directions.

## III. PROPOSED METHODOLOGY

### A. Algorithm Design

The proposed approach combines AI techniques from recent studies with new AI methods for improved trajectory reconstruction using a main algorithm and three core procedures. Each step of the reconstruction process solves a particular challenge.

The process begins with the input: Raw AIS trajectory data.

**Step 1: Denoising and Gridding**

After removing noise from the raw AIS data using Geohash-DTW, we use U-Net to create a clear and grid-based trajectory.

**Step 2: Extraction of features**

To improve model performance, the most pertinent features are chosen from the trajectory data using Ant Colony Optimization.

**Step 3: Gap filling**

Two methods are used to rebuild missing segments in the trajectory: Geohash-DTW for long gaps and kinematic interpolation for short gaps.

**Step 4: Temporal Refinement**

A BiGRU model is used to improve timestamp accuracy, and a Genetic Algorithm is employed for adjusting the model's parameters.

Figure 1 illustrates the entire process of our trajectory reconstruction framework.

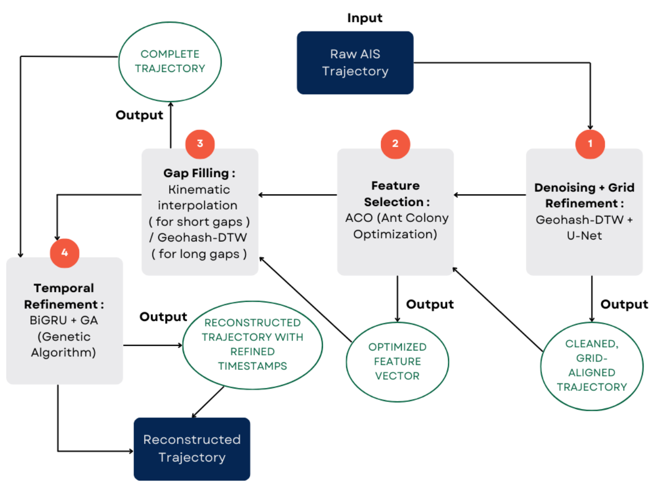


Fig. 1: The Proposed Hybrid Trajectory Reconstruction Framework

### B. Hybrid Trajectory Reconstruction Framework using AI techniques

This algorithm presents the principal method of the framework. It takes a raw trajectory as input and processes it through three stages: denoising, feature selection and trajectory reconstruction with refinement. The algorithm needs a number of important inputs:

$T_{\mathbf{raw}}$ **:** The raw AIS trajectory data containing noise and gaps.

$\tau$ **: Gap length threshold :** A predefined value to distinguish between short and long gaps, to choose whether to use

Geohash-DTW or kinematic interpolation for reconstruction.
**params :** A set of configuration parameters that include :
**GeohashPrecision** determines how detailed the map is devided during the denoising process. The higher the precision, the smaller the grid cells, which helps to better identify and remove noise in the trajectory.
**ACOiterations:** The number of iterations for the Ant Colony Optimization to select optimal trajectory features.
**GAgenerations:** The number of generations for the Genetic Algorithm to optimize hyperparameters of the BiGRU and U-Net models.
**U_Net_model:** A pre-trained convolutional neural network employed to refine and denoise the raw trajectory data during the denoising process.

**Algorithm 1** Main Algorithm: Hybrid Trajectory Reconstruction

**Inputs**:
$T_{\text{raw}}$ : Raw AIS trajectory (with noise and gaps)
$\tau$ : Gap length threshold
params : {GeohashPrecision, ACOiterations, GAgenerations}
U_Net_model : Pre-trained U-Net model for trajectory refinement
**Output**:
$T_{\text{reconst}}$ : Reconstructed, denoised, and time-aligned trajectory
$T_{\text{clean}} \leftarrow \text{Denoising}(T_{\text{raw}}, \text{params.GeohashPrecision}, \text{U\_Net\_model})$
$F_{\text{opt}} \leftarrow \text{FeatureSelection}(T_{\text{clean}}, \text{params.ACOiterations})$
$T_{\text{reconst}} \leftarrow \text{ReconstructionAndRefinement}(T_{\text{clean}}, F_{\text{opt}}, \tau,$ params.GAgenerations$)$
**return** $T_{\text{reconst}}$

### C. Denoising using Geohash-DTW and U-Net

This procedure detects and removes noisy segments using Geohash encoding and Dynamic Time Warping (DTW). It also prepares the cleaned data for processing by converting it into a grid format and using a U-Net for spatial refinement. The following is a brief description of the primary parameters used in this denoising step :
**Precision :** Sets how detailed the Geohash grid will be. Smaller grid cells indicate a higher value, which facilitates the identification and elimination of small and noisy segments in the trajectory.
$\theta_{\textbf{noise}}$ **:** A threshold used with DTW to decide if a segment is too different from a normal one. If the distance is higher than this threshold, the segment is marked as noisy.
**H :** A reference segment that shows what a normal trajectory should look like. It is used to compare it with current segments during the noise detection process.
**Rasterize** allows the U-Net model to interpret the filtered trajectory data spatially by transforming it into a 2D grid format. In order to make sure that the output keeps its original structure while adding the denoising improvements, **derasterize** later converts the revised grid back into a trajectory format.

**Algorithm 2** Denoising Procedure: Geohash-DTW + U-Net

**Inputs**:
$T_{\text{raw}}$ : Raw trajectory (with noise and gaps)
precision : Geohash precision
U_Net_model : Pre-trained U-Net model for trajectory refinement
**Output**:
$T_{\text{clean}}$ : Denoised and refined trajectory
$T_{\text{geohash}} \leftarrow \text{GeohashEncode}(T_{\text{raw}}, \text{precision})$
**for each** segment $s$ **in** $T_{\text{geohash}}$ **do**
  **if** $\text{DTW}(s, H) > \theta_{\text{noise}}$ **then**
    Mark $s$ as noisy
  **end if**
**end for**
$T_{\text{filtered}} \leftarrow T_{\text{raw}}$ without the noisy segments
$G_{\text{grid}} \leftarrow \text{Rasterize}(T_{\text{filtered}})$
$G_{\text{refined}} \leftarrow \text{U\_Net\_model}(G_{\text{grid}})$
$T_{\text{clean}} \leftarrow \text{Derasterize}(G_{\text{refined}})$
**return** $T_{\text{clean}}$

### D. Feature Selection using Ant Colony Optimization

As described in algorithm 3, the metaheuristic ACO was developed to address challenging combinatorial optimization issues. It takes inspiration from the way actual ants behave, especially how they can create and follow pheromone trails to communicate [14]. ACO is used to search and select in a probabilistic way the most relevant trajectory features. The chosen features are optimized for minimizing reconstruction error across generations. The main parameters employed in this step are explained below :
$\varphi_i$ **:** The reconstruction error measured by RMSE for the feature subset chosen by ant $a_i$. It helps to decide how good the solution is.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2}$$

where $y_j$ is the true value and $\hat{y}_j$ is the predicted value.

**Pheromones :**Values that help guide what features the ant chooses in the next round. If a set of features gives a lower RMSE, it leaves stronger pheromones so it is more likely to be chosen again.

**Algorithm 3** Feature Selection using ACO Procedure

**Inputs**:
$T_{\text{clean}}$ : Cleaned trajectory
ACOiterations : Number of iterations for Ant Colony Optimization
**Output**:
$F_{\text{opt}}$ : Optimal subset of features
Initialize ants with random subsets of features
**for** $i \leftarrow 1$ **to** ACOiterations **do**
  **for each** ant $a_i$ **do**
    $F_i \leftarrow$ probabilistic selection of features
    $\varphi_i \leftarrow \text{RMSE}(\text{Reconstruct}(T_{\text{clean}}, F_i))$
    Update pheromones based on $1/\varphi_i$
  **end for**
**end for**
$F_{\text{opt}} \leftarrow \arg\min_F \text{mean}(\varphi_1, \ldots, \varphi_n)$
**return** $F_{\text{opt}}$

### E. Trajectory Reconstruction and Temporal Refinement

As shown in algorithm 4, this final procedure handles both short and long gap reconstruction. Kinematic interpolation is applied for short gaps and Geohash-DTW is used for long gaps along with the selected features. After reconstruction, a BiGRU refines temporal consistency and the hyperparameters of the BiGRU and U-Net models are optimized using a GA. Below is a quick explanation of some parameters that are used in this process :

$v$ and $a$ : If the gap is small (length$(G_i) \leq \tau$), the velocity $v$ and acceleration $a$ at the gap's boundaries are used to interpolate the missing data.

$C$ : If the gap is large (length$(G_i) > \tau$), a set of candidate paths ($C$) is generated using Geohash-DTW. These paths represent possible movements during the gap.

$c_{\text{best}}$ : From the candidate paths, the best path is selected based on Dynamic Time Warping and the optimization filter $F_{\text{opt}}$.

**Algorithm 4** Reconstruction And Refinement Procedure

```
Inputs:
    T_clean, F_opt, τ, GAgenerations
Output:
    T_aligned
for each gap G_i in T_clean do
    if length(G_i) ≤ τ then
        Interpolate with boundary estimates of v and a
    else
        C ← candidate paths via Geohash-DTW
        Filter C with F_opt; select c_best by DTW
        Fill gap with c_best
    end if
end for
T_grid ← reconstructed grid from filled gaps
T_denoised ← U_Net(T_grid)
T_aligned ← BiGRU(T_denoised)
Optimize U-Net and BiGRU with GA over GAgenerations
return T_aligned
```

## IV. Illustrative Example of AIS Data and Preprocessing

We provide a small synthetic example that matches the typical AIS data attributes and preprocessing methods to help conceptually validate our reconstruction pipeline. In this dataset, around 180,000 AIS messages are collected over a 24-hour period from 12 vessels, including cargo and tanker kinds. With sample intervals ranging from 2 to 10 seconds, each AIS report includes a timestamp, latitude, longitude, speed over ground (SOG), and course over ground (COG). Common AIS imperfections are included in the dataset, such as:

- Inaccurate readings of speed (such as exceeding 35 knots for cargo vessels).
- Missing intervals of 30 seconds to 5 minutes.
- Irregular coordinates.

Some of the preprocessing steps are:

- Outlier testing and basic validation.
- Geohash encoding at precision level 6 for spatial discretization.
- Normalizing features prior to providing the model with data.

This example serves as an outline for future tests using real-world datasets and demonstrates the common data errors our framework aims to work on.

## V. Conclusion and Future Directions

### A. Conclusion

In conclusion, the proposed methodology combines current research in trajectory reconstruction with new contributions using AI approaches such as ML and DL ; the use of Ant Colony Optimization for feature selection. The framework has Geohash-DTW for noise removal, because better results appear when using clean data. Then, ACO for the objective of feature selection and kinematic interpolation with Geohash-DTW for reconstruction (depending on short or long gaps), with biGRU, GA and hybrid methodology performing temporal refinement. As shown in the comparative table in the literature review section, each method has its strong points and limitations, that's why, we propose combining these methods to address the gaps and enhance the overall performance.

### B. Future Work

This study presents a fully theoretical framework for reconstructing hybrid maritime trajectories. We intend to evaluate this idea using actual AIS datasets in the future. A numerical comparison with other methods (not only qualitative) would be a valuable next step to validate the superiority of the proposed approach. This will involve a dataset preparation process and also a comparison with current methods. We strongly believe that this combination will create a robust trajectory reconstruction for vessels that will be a force for decarbonization as well as the creation of a sustainable maritime environment. Consequently, it will also enhance ETA prediction accuracy.

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