# A NEURAL NETWORK APPROACH TO PREDICT MARINE TRAFFIC

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# Abstract

The marine traffic has been significantly rising fast during the last period of time. One of the most important problems for prediction of the marine traffic is to find certain patterns movements of vessels. Even the modern navigation devices could not ensure full maritime picture in narrow waterways because of geographical structures and various disturbances. Moreover, all vessels have could not use autopilot in straits for these reasons; they have to operated manually according to rules. The vessels turning points could be used to predict of marine traffic.

# Contents

# 1  Introduction

The increased demand for marine traffic safety and security issues become more important to predict maritime traffic. The establishment of intelligent monitoring and predicting systems for marine traffic is becomes more essentially due to vessels congested zones.  The main issue of such intelligent maritime traffic monitoring and prediction system is to predict vessel route for all her journey (Fig.  1). For this purpose could be used information from vessel's Automatic Identification system (AIS). Otherwise this system holds essential information about port of destination for prediction of route but not about turning regions. So we need predict all turning regions of route and it could dramatically decrease the risk of marine transportation.
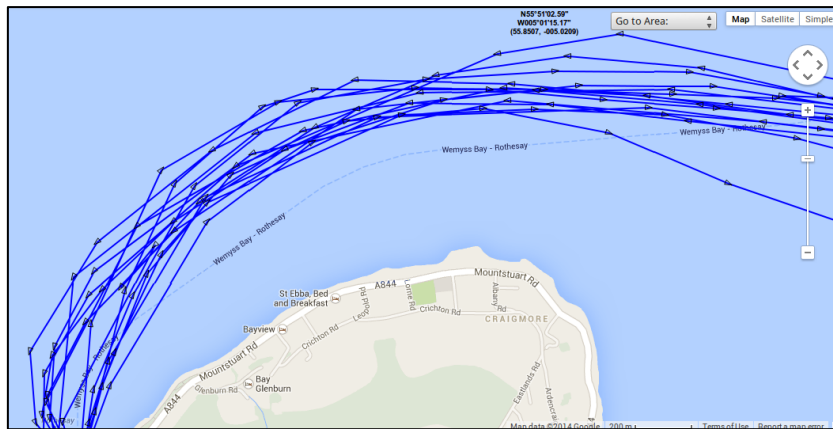


*Fig.  1 The route to the same port [1]*

The EU Directive 2002/59 is further structured in the following subdivisions to incorporate the intelligent maritime traffic monitoring tasks and to improve maritime safety and security capabilities:

1. development of the SafeSeaNet project that consists of a pan-European electronic information system for ocean navigation and cargo handling;
2. collaboration among the EU member states and the respective maritime authorities to face maritime issues and challenges;
3. coordination of maritime activities around the EU coastline f or the vessels in distress;
4. development on the long distance automatic identification system (AIS) with the International Maritime Organization (IMO) [1] and the International Association of Marine Aids to Navigation and Lighthouse Authorities;

5. Development on the shore-based traffic monitoring infrastructure database system with the IMO.

Therefore, despite the considerable amount of intelligent features developed for air [3] and land transportation [4] systems to improve the navigation safety and security, those facilities are still under developed for vessel navigation systems. However, the maritime surveillance systems have many challenges [5].

In this paper is proposed the model of intelligent maritime traffic predicting system. This system mission is tracking and predicting vessel's turning points. This solution will be originated by clustering turning regions and find route certain patterns with Artificial Neural Network.

To achieve these goals, the model of intelligent prediction for marine traffic will be created. This model has been supported by a huge amount of real data.

## 2  Marine traffic monitoring challenges

The marine traffic is controlled by Vessel Traffic Services (VTS) (Fig.  2). VTS works of securing the navigation of vessels passing traffic separation schemes and warning them against any possible collision and accident. Conventional VTS are equipped with several marine surveillance mechanisms for the same purpose: radars, automatic plotting aid (ARPA), AIS and long-range identification and tracking (LRIT) systems. Moreover, lasers, sonar and infrared detection could be used too. Furthermore, more information-based navigation aids are used – the Global Positioning System (GPS), electronic charts, satellite tracking and others.
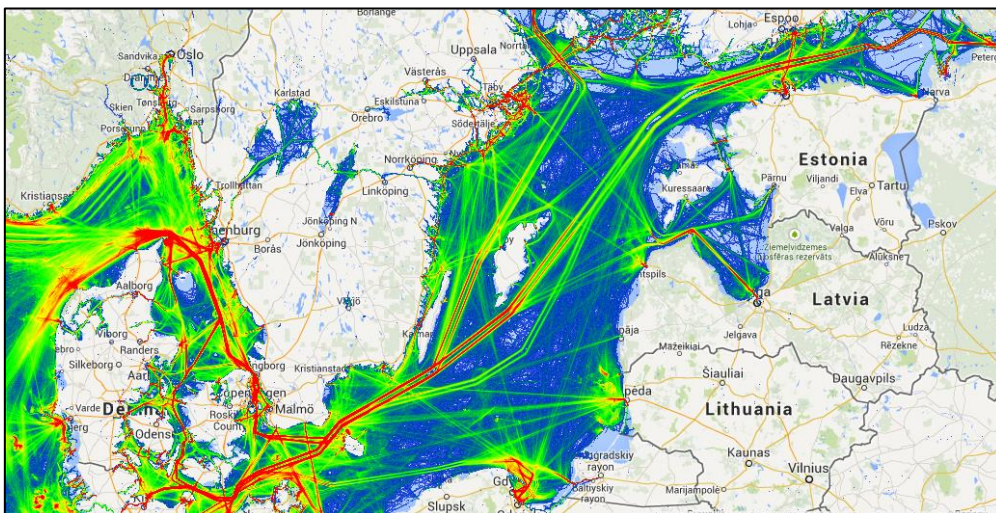


*Fig.  2 Marine traffic in the Baltic Sea [1]*

However, the marine traffic is controlled by using the traditional hardware of navigation aids – lights, buoys, channel markers. The authority is always seeking new ways to attain the maximum benefit from information technology [6].

Otherwise, there are many challenges faced by such maritime surveillance systems [7]:

1. Huge amount of surveillance territory;
2. Large number of targets;
3. Multi target observations;
4. Noisy signal and geographical structures;
5. Propagation of radio waves.

Moreover, the marine traffic congestion zones are biggest challenge for such systems. These zones usually are in harbors, straits and channels. The reasons of marine traffic congestion can be declared as:

• The vessels with low sailing velocity and speeding up and down frequently,

• The vessels with disorder navigation,

• Overcrowded straits and channels.

Furthermore, these challenges raise the level of risk of accidents at sea. This risk level can be quantified by Eq, (1)

$$P(x \geq N | N \geq 1) = f_N = \frac{\sum_N^{max} P(fatality)}{\sum_1^{max} P(fatality)} \tag{1}$$

Where N is the number of expected number of deaths and f_N is the probability that the number of deaths resulting from an accident will be more than N.

Therefore, these challenges could be overcome by exploiting artificial neural network. Further developments of intelligent marine traffic monitoring and predicting systems are fundamental and essential to the marine traffic management automation. Moreover, the maritime surveillance systems incorporated with intelligent can analyze information fusion, prediction of danger situations, traffic flow estimation and etc. It is especially important for traffic safety, navigation efficiency and for future developments.

# 3 Marine Background of AIS

The AIS is vessel tracking system is used on vessels and by authorities – VTS, Naval. International Maritime Organization's International Convention for the Safety of Life at Sea requires AIS to be fitted aboard international voyaging ships with gross

tonnage (GT) of 300 or more tons, and all passenger ships regardless of size. This system is identifying and locating vessels in the sea. VHF is used for periodically broadcast vessels data (International Maritime Organization number, position, course, speed and etc.) by electronic messages. AIS integrate with positioning systems (GPS) and with navigation sensors, such as a gyrocompass and rate of turn indicator (Fig. 3). These messages are transmitted directly to AIS receivers which are in vessels and VTS Base stations.  Received messages could be displayed on ECDIS or on Radar monitor. Moreover, vessels which have AIS transmitter could be tracked by VTS along coast line. Typically AIS transmitters range is 20-30 nautical miles it is depends on VHF radio range. When the vessels are out of range vessel could be tracked with special satellites that are fitted with AIS receivers [8]. The implementation plan and requirements for AIS are outlined in Subparagraph 2.4 of Regulation 19 of Chapter V of the International Convention for the Safety of Life at Sea (SOLAS) [9]. The system has been mandatory on all new ships in international traffic since 1 July 2002, and ended on 2004 include all passenger ships, tankers and other ships of 300 tons engaged in international voyages. Fully implemented in 2008, the system will also cover all ships of 500 tons or more in national voyages. The requirements state that: "AIS shall:

Provide automatically to appropriately equipped shore stations, other ships and aircraft information, including the ship's identity, type, position, course, speed, navigational status and other safety-related information (Fig.  3);

Receive automatically such information from similarly fitted ships;

Monitor and track ships;

Exchange data with shore-based facilities.

AIS shall be operated taking into account the guide-lines adopted by the Organization. Ships fitted with AIS shall maintain AIS in operation at all times except where international agreements, rules or standards provide for the protection of navigational information." Ships covered by regulation 19 are defined as SOLAS Class A ships, and a mobile AIS station is mandatory on these ships. Work is also under way at IEC to develop an equipment recommendation for SOLAS Class B ships [8], but AIS on these ships is at present not mandatory. The two frequencies used for AIS worldwide are 161.975 and 162.025 MHz (channels 87B and 88B, or AIS1 and AIS2) [10].
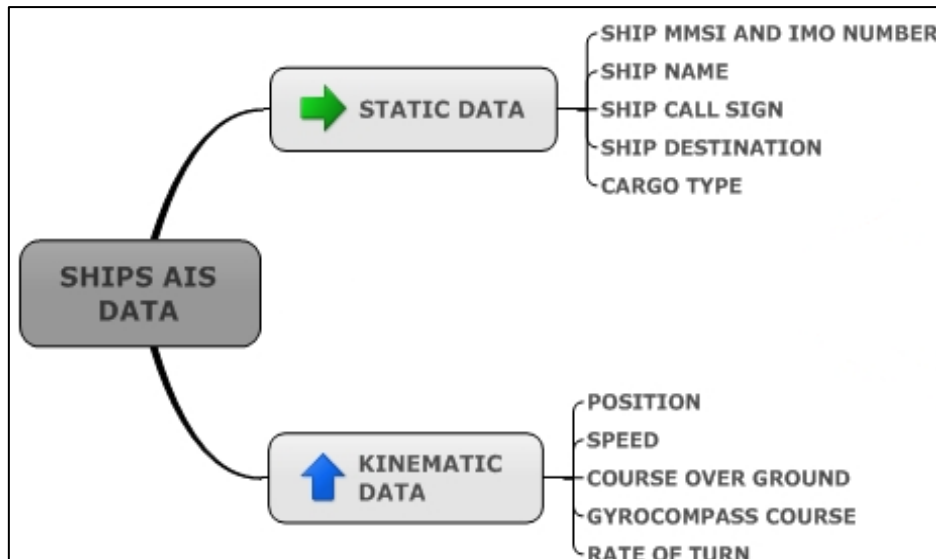
*Fig. 3 AIS data types*

The kinematic data are transmitted at frequent intervals of approximately 3-10 s. Therefore, some important parameters for collision avoidance can be calculated:

1. The closest point of approach (CPA);
2. Time to closest point of approach (TCPA);

These two indicators most widely are used to avoid collision at sea. Correspondingly, the AIS are providing data which is especially important for traffic safety, navigation efficiency.

# 4   DBSCAN: density-based clustering algorithm

(Density-Based Spatial Clustering of Applications with Noise) is a density based clustering algorithm [14]. The algorithm grows regions with sufficiently high density into clusters and discovers clusters of arbitrary shape in spatial databases with noise. Density-based clustering defines cluster as region, the objects of the region are dense. The clusters are separated from one another by low-density regions [15]. The reason we choose density-based clustering is that it has significant advantages over partitioned and hierarchical clustering algorithms. It can discover clusters of arbitrary shapes. The computational complexity can be reduced to O ($n$lgn) by building some special data structures. In addition it is able to effectively identify noise points (Fig. 5) [16].
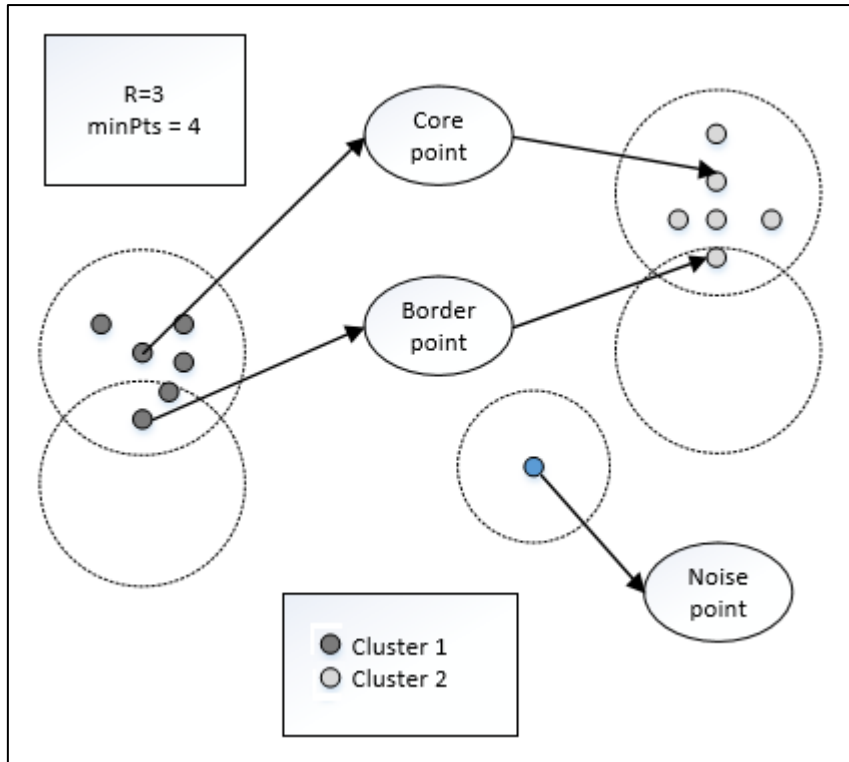
*Fig. 3 DBSCAN clustering algorithm*

But density-based clustering algorithms easily lead to memory problem when facing large databases. Some researches show that current density-based clustering algorithms often have difficulties with complex data sets in which the clusters are different densities [17]. As a kind of density-based clustering, the DBSCAN algorithm was first introduced by Ester, et al. Some basic concepts related with DBSCAN are as follow [18]:

$$d(x_i, x_j) = \left( \sum_{k=1}^{m} (x_{ik} - x_{jk})^2 \right)^{\frac{1}{2}} \tag{2}$$

The key idea in DBSCAN is that for each data object of a cluster, the neighborhood of a given radius ($\varepsilon$) has to contain at least a minimum number (MinPts) of objects [19][18].

# 5 Artificial Neural Network

Artificial Neural Networks (ANN) simulates the processes of the human brain (Fig. 6). The ANN makes associations between varieties of the information. The ANN realizes as intuitive reasoning rather than the logical reasoning normally executed by machine. The main advantage of ANN is to incorporate uncertainty as well as data which is dynamic character has led to a number of studies to establish its applicability to predict marine traffic.
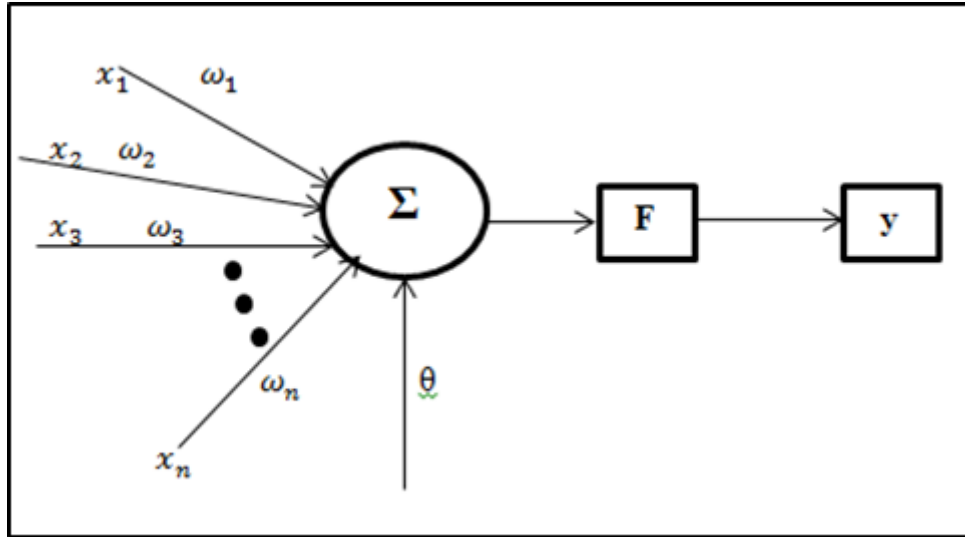
*Fig. 4 Artificial Neural Network*

$$y = F(\sum_{i=1}^{n} x_i * \omega_i - \theta); \qquad (3)$$

One of the ANN scheme is the back-propagation (BP) network [20]. The back-propagation neural network architecture is designed by fully interconnected layers or rows of processing units. The inter connections are called weights, and provide the means for the ANN to save knowledge, the process of A learning B. Also, the errors are calculated during this process. These errors are used to back-propagated from the output neurons to all the hidden neurons; so all the weights are adjusted by the errors. This learning process continues till the error is reduced to specified minimum values. After that the weights are saved as ANN knowledge. The weights are used to perform information processing operation by back-propagation algorithm. The ANN may have as large numbers of neurons as it needed. Likewise, the number of layer is exchangeable. The ANN behavior depends on the simple activation function which could be a linear or a non-linear. The ANN knowledge is training by pre-mined data and weights are saved. Moreover, The ANN has the capability to learn with any complex structure of data. So, the ANN is capable to implement a learning algorithm and made decision support ability of marine traffic prediction.

## 5.1  Artificial Neural Network development for marine traffic prediction

A three-layer neural network model (Fig.  7) was developed to predict the turning regions of vessels in marine traffic. The ANN inputs were vessels:
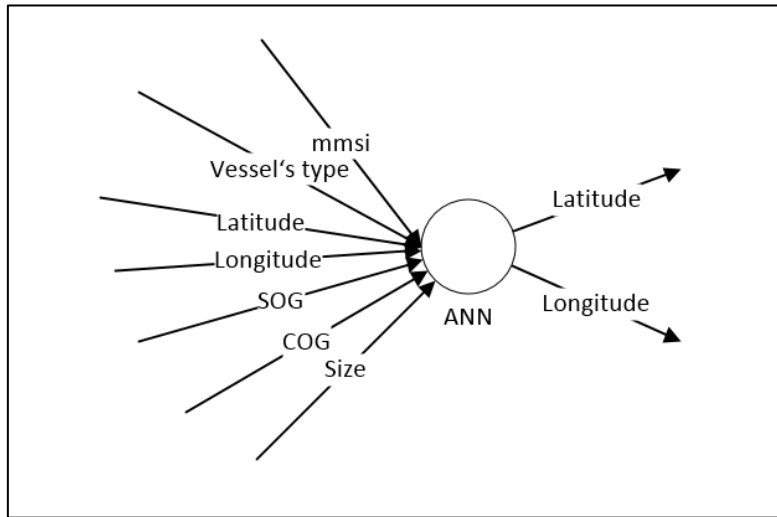
1.  Latitude of turning regions;

2. Longitude of turning regions;

3. speed;

4. course;

5. MMSI number;

6. Dimension (length & width);

7. Type of vessel.

The ANN outputs were used to predict the next turning regions. The ANN outputs:

1. Latitude of next turning region;

2. Longitude of next turning region;

The ANN was fully connected and every neuron connected to second layer neuron [21].



*Fig. 5 Artificial Neural network for marine traffic*

The output of each neuron was calculated by an activation function. All the inputs were summed by neurons with threshold. To develop the ANN, the pre-mined data was divided into two parts: 90% of turning points were used to train the ANN and the rest of observations were used for validation. All data was normalized to common interval of [-1, 1].

The algorithm was solved by python 2.7 (used the implementation of [22]) with neuron package [23]. The relationship between the output ($y_t$) and the inputs ($y_{t-1,...,}y_{t-p}$) has following mathematical representation:

$$y_t = w_0 + \sum_{j=1}^{Q} w_j g \left( w_{0j} + \sum_{i=1}^{p} w_{ij} y_{t-1} \right) + e_t, (4)$$

Where $w_{i,j}$ ($i = 0, 1, 2, ..., P, j = 1, 2, ..., Q$) and $w_j (j = 0, 1, 2, ..., Q)$ are model parameters often called connection weights; P is the number of input nodes; is the

number of hidden nodes; – is the residual of model at time t, and g is the transfer function. The activation function is often used as the hidden layer transfer function. That is,

$$Sig(x) = \frac{1}{1+\exp(-x)};$$ (5)

Once a network structure (P, Q) is specified, the network is ready for training, a process of parameter estimation. The parameters are estimated such that the cost function of neural network is minimized. Cost functions an overall accuracy criterion such as the following mean squared error:

$$E = \frac{1}{N}\sum_{n=1}^{N}(e_j)^2 = \frac{1}{N}\sum_{n=1}^{N}\left(y_t - \left(w_0 + \sum_{j=1}^{Q} w_j g\left(w_{0j} + \sum_{i=1}^{p} w_{ij}y_{t-1}\right)\right)\right)$$ (6)

Where N is the number of error terms. This minimization is done with some efficient nonlinear optimization algorithms other than the basic propagation (Figure 3.) training algorithm.

After the artificial neuron network receives the inputs, it will propagate them from the input layer (Fig. 6) through the hidden layers to the output layer, where the responses are obtained.
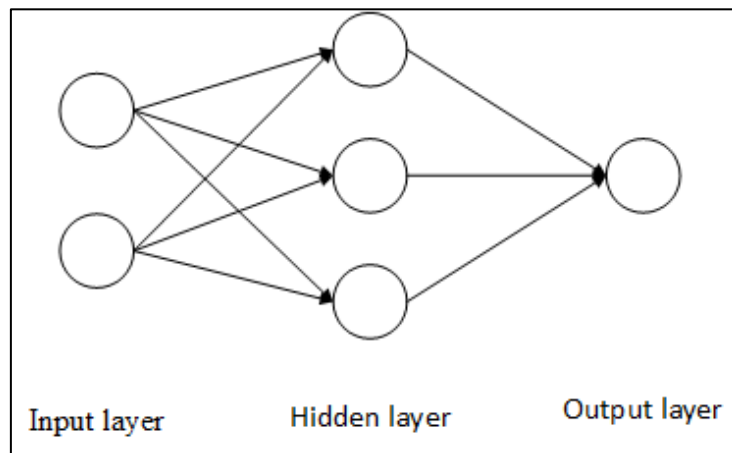


**Fig. 6 Artificial neuron network layers**

This artificial neuron network learning process deals with speed of convergence and the local minima.

## 5.2 ANN training

The data used for training the ANN was collected from marinetraffic.com website and was stored in MySQL database. These data covered whole Baltic Sea, so mean count of vessels was 3000 on a time step of 180 seconds.

The data was filtered by change of course to calculate vessel turning regions and vessel's speed. If vessel's course was changed more than 4° it is turning point of vessel's route. Likewise, vessel's which have less than 4 knots of speed weren't monitored. Monitoring lasted 10 days. More than 300,000 turning points, 30,000 vessels and 6,000 destinations were stored during this period.

So, turning points data like latitude and longitude, vessel's type, course, speed, size and MMSI was stored in database (Fig. 7). These data used to train the Artificial Neural Networks. The trained ANN has been used to predict next position of turning point (latitude & longitude). Moreover, the trained ANN has been used to predict whole route of vessel to port of destination. All stored data considered to decide model structure and used for training of ANN.



*Fig. 7 Turning points on the vessel's route [1]*

The sampling stored period of 180 seconds was chosen because of maneuver performance of vessels. In this respect, three-minute-ahead positions are predicted by utilizing past data of vessel. The following ANN model has been trained and analyzed for the best performance.

In the neural network architecture, one hidden layer with sigmoid activation function has been used. The numbers of hidden neurons and hidden layers have been found by trial and error using collected data to obtain the best performance. Training and prediction processes are realized at 4 steps as explained below:

1. Collecting data for training;
2. Determination of Neural Network architecture and models;
3. Training of Neural Network;
4. Testing the trained Neural Network.

# 6   Proposed model development

The proposed model has two main parts:

1. Clustering turning regions by DBSCAN algorithm;
2. The ANN learning clustered turning points;

Clustering data was implemented by Scikit-learn's [24] python library. This library requires the input of a distance matrix showing pairwise distances between all turning regions in the dataset. So, the DBSCAN algorithm requires two parameters: $\varepsilon$ (epsilon) and the minimum number of points required to form a cluster (minPts). Parameter $\varepsilon$ depends on radius of cluster. It could not be equal for whole route because of narrow channel, harbors and etc. (Fig. 8).
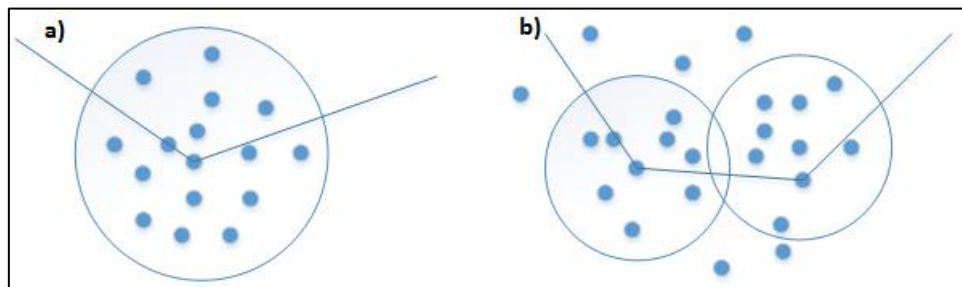


*Fig.  8 clustering turning regions with the some ε parameter*

Therefore, the parameter $\varepsilon$ is different for open seas, harbors, straits and channels (Fig.  8). In order to get optimal clusters the proposed model calculates different parameter $\varepsilon$ four times. It calculates $\varepsilon$ from biggest possible value and reduced on every cycle to minimize possible error (Fig. 11).
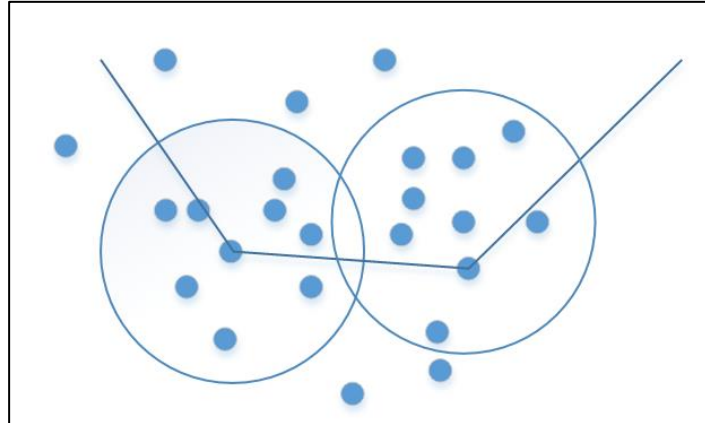
*Fig.  9 Clustered turning regions with minimized ε*

So the aim of this study is to identify turning point zones by investigating the marine traffic turning points.

As a second part of model is the ANN (Fig.  10). The model was created by the three- layer neural network structure with a sufficient number of neurons in the hidden layer and enough learning time can theoretically model any nonlinear functions at any accuracy. However, the questions in practical implementation are the selection of training algorithm, number of hidden neurons, learning rate, and momentum, to guarantee that the error converges to a desired value.
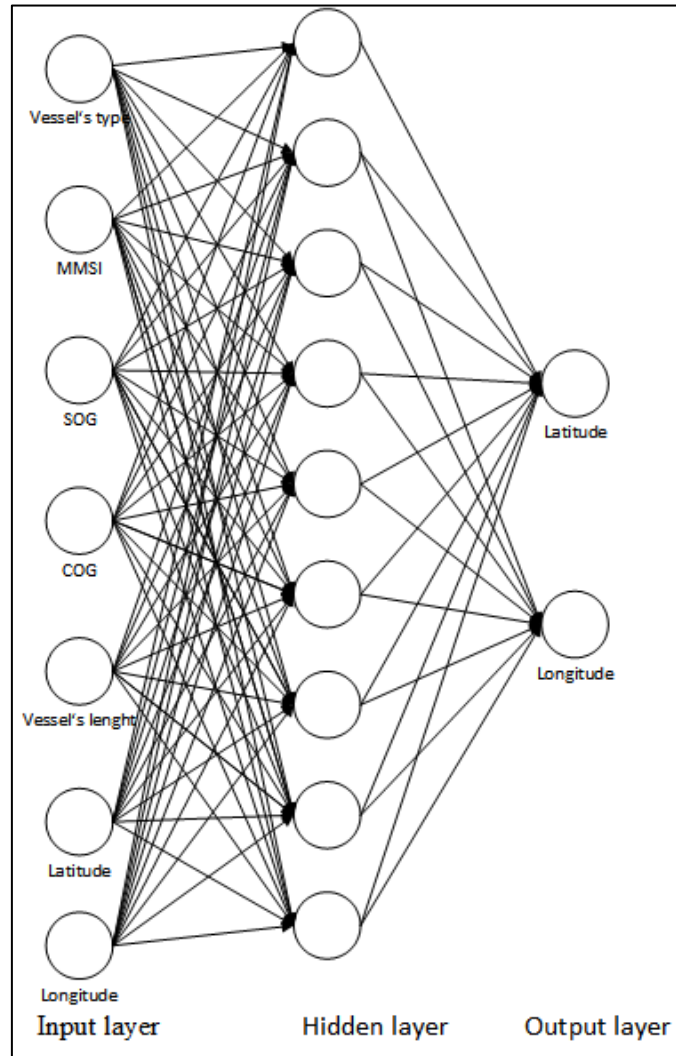
*Fig. 10 Model of ANN*

The learning rate was chosen by trial and error to be 0.0009. If the learning rate was too large, oscillation or divergence occurred, whereas a small learning rate resulted in a slow training process without improvement in the accuracy of the proposed model. The training process was terminated when the half-sum of the squared error reached a threshold value of 23. This threshold corresponded to prediction accuracies above 99% for the training data-set.

For the three-layer neural network model, the number of input neurons was determined by five environmental factors that affect survival and growth, and the number of output neurons was set by the two classifications (i.e. survival/death and growth/no-growth). The numbers of neurons in the hidden layer can be selected with flexibility but the number determines how well a data-set is trained. Too many hidden neurons lead to a data-set-specific relationship between inputs and outputs, or an ''over-fitting'' problem. With smaller numbers of hidden neurons, the network may

not have adequate power to learn the patterns with satisfactory accuracy, resulting in an ''under-fitting'' problem.

## 6.1 Block diagram of proposed model

Fig. 11, describes the proposed approach for clustering turning points (a part) and learning the ANN by clusters.
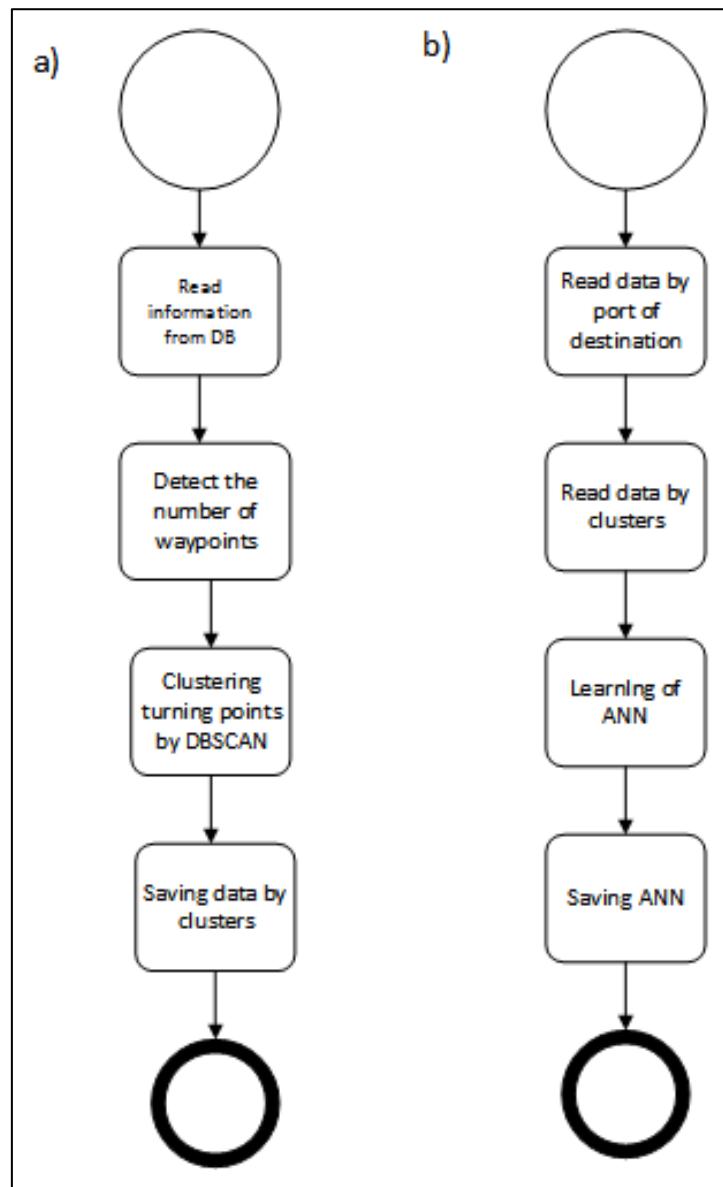


Fig. 11 Block diagram of proposed model

As shown in Fig. 11, the proposed model consists from two main parts:

1. Clustering points of route;
2. Learning the ANN by clusters.

The proposed model begins from reading turning points information from database. This information is used to clustering all turning points by DBSCAN algorithm.

The ANN starts learning by clusters. The ANN after training was completed neurons weights are saving by clusters. These neuron weights are used to predict next turning points by clusters.

# 7 Prediction marine traffic with proposed model

The ANN after training was completed; input-output vectors have been modified as explained above for prediction step with ANN model, as shown in Fig. 12.
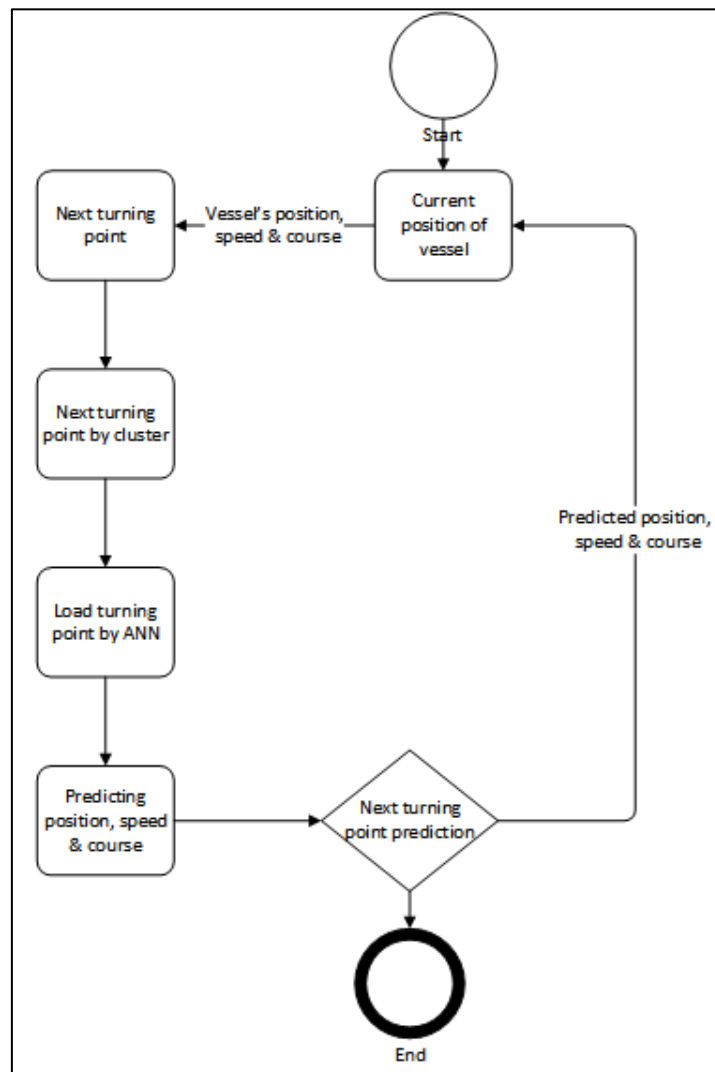


*Fig. 12 proposed model for prediction vessel's route*

The proposed ANN model for prediction of turning points are using calculated weights by neurons. These could be done by geeting current position of vessel. Next

step would be calculate nearest turning point. It clould be done by calculating distance (7, 8, 9,10) to nearest cluster.

$$a = sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos(\varphi_1) * \cos(\varphi_2) * sin^2\left(\frac{\Delta\lambda}{2}\right) \tag{7}$$

$$c = 2 * atan2(\sqrt{a}, \sqrt{(1-a)}); \tag{8}$$

$$d = R * c \tag{9}$$

$$\theta = atan2(\sin(\Delta\lambda) * \cos(\varphi_2), \cos(\varphi_1) * \sin(\varphi_2) - \sin(\varphi_1) * \cos(\varphi_2) * \cos(\Delta\lambda)); \tag{10}$$

This uses the 'haversine' formula to calculate the great-circle distance between two points – that is, the shortest distance over the earth's surface – giving an 'as-the-crow-flies' distance between the points. Midpoints of cluster are used to find nearest cluster and current vessel position. Midpoint is calculated by:

$$B_x = \cos(\varphi_2) * \cos(\Delta\lambda); \tag{11}$$

$$B_y = \cos(\varphi_2) * \sin(\Delta\lambda); \tag{12}$$

$$\varphi_m = atan2(\sin(\varphi_1) + \sin(\varphi_2), \sqrt{((\cos(\varphi_1) + B_x)^2 + B_y^2)}; \tag{15}$$

$$\lambda_m = \lambda_1 + atan2(B_y, \cos(\varphi_1) + B_x); \tag{13}$$

Where $\varphi$ is latitude, $\lambda$ is longitude, R is earth's radius (mean radius = 6,371km);

Moreover, course must coincide with bearing (11,12,13) to calculated nearest cluster. Determinated cluster are used to load the ANN for calculation. Therefore, every cluster have own ANN with calculated weights. The ANN loaded with vessel parameters (current position, course, speed, MMSI number, vessel type & vessel particulars) predict next turning point (latitude & longitude).

Usually, the vessel route consists of many turning points. The method has particularly been formed for prediction of points of turning but the same way could be used for predicting all route of vessel. As shown in Fig. 13, the ANN used as many times as it needed.
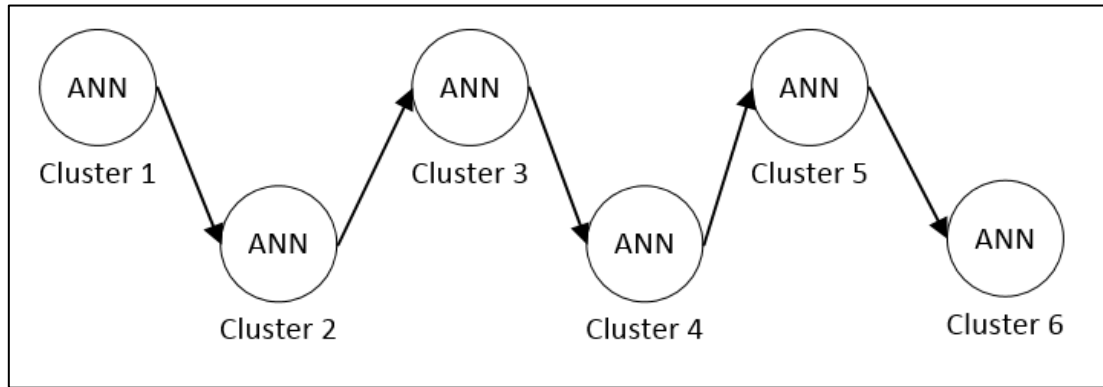
*Fig. 13 Vessel's route prediction by clusters*

So, the ANN could use predicted turning point for predict next turning point (Fig. 14) and repeat this to port of destination.
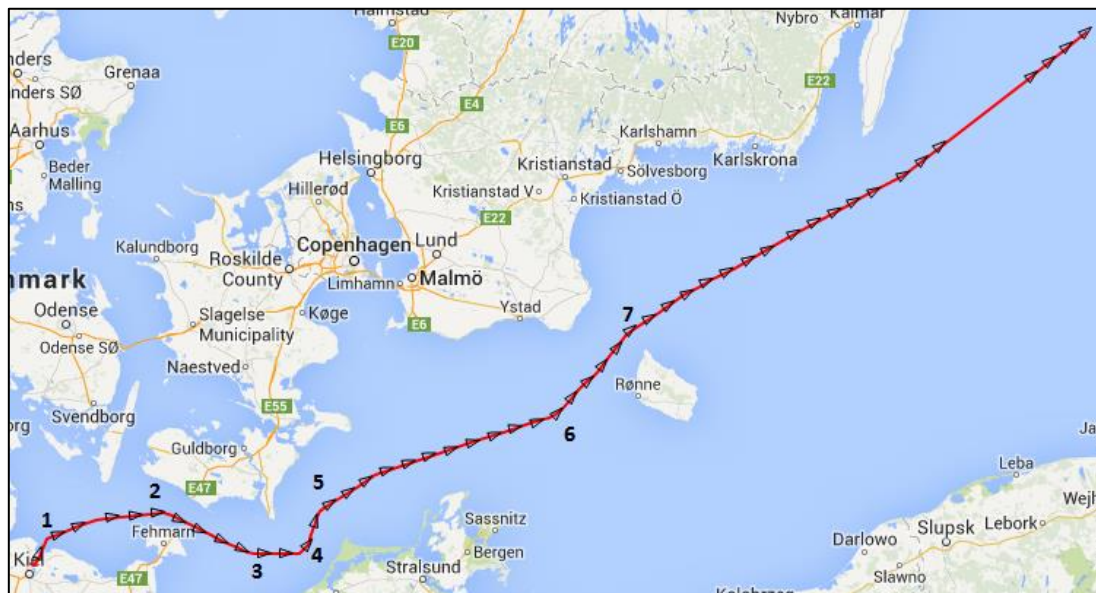


*Fig. 14 Route prediction*

As shown in Fig. 14 the route could be divided by turning regions. This region is different for vessels but it could be united by clusters.

## 8 Clustering results

A large amount of traffic flow information was used. This information obtained from marinetraffic.com by collection equipment such as AIS, are recorded and accumulated in the database of proposed model. However, the data was filtered by turning points (4° change of vessel course). Data preprocessed to sort by port of destination. After this procedures have got data set for proposed model. Test data in this paper contains turning point by port of destination as shown in Fig. 15.
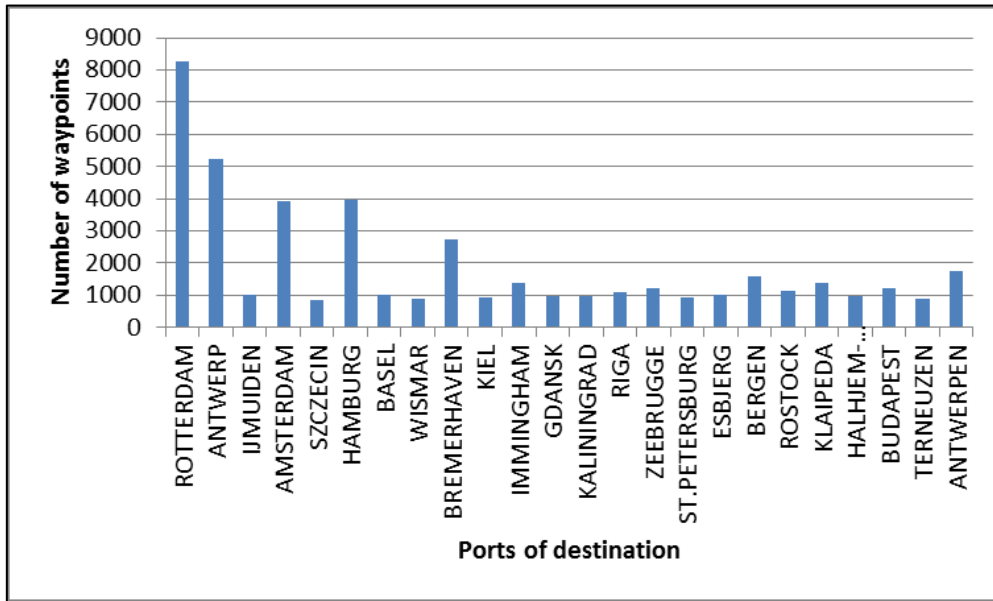
**Fig. 15 Number of turning regions by port of destination**

This data set was clustered by DBSCAN algorithm. As a result we got clusters sorted by port of destination as shown in Fig. 16. Rotterdam as most popular port have largest amount of clusters.
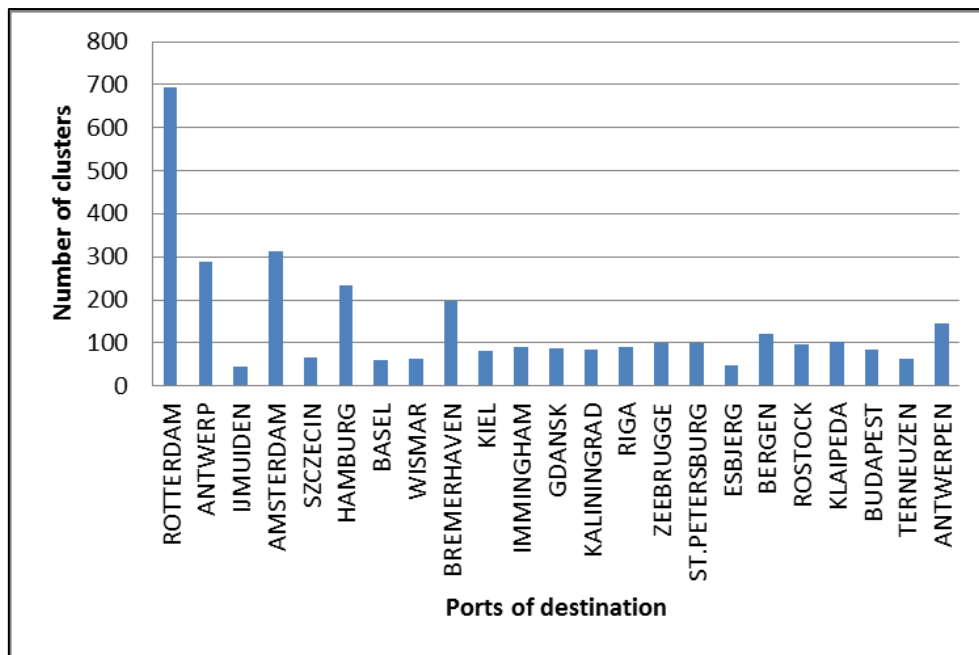


*Fig. 16 Number of clusters by port of destination*

Number of turning points depends on DBSCAN clustering parameter $\varepsilon$. A cluster size depends on turning points count.

# 9 Artificial Neural Network results

The neural network model correctly predict vessel route. The precision of ANN prediction depends on cluster size and it directly depends on DBSCAN algorithm parameter ε. The distance between real turning point and predicted turning point do not exceed cluster diameter (parameter ε) (Fig. 17).
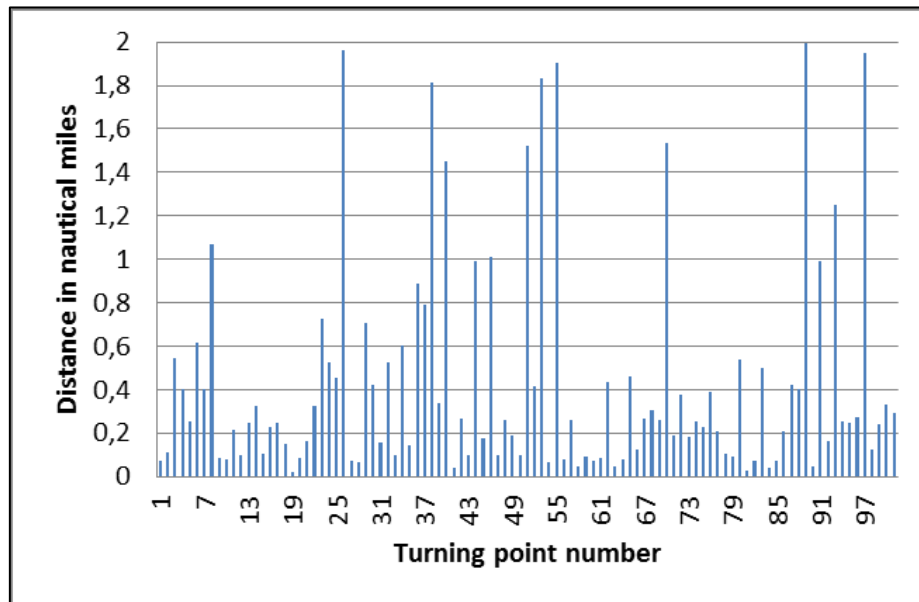


*Fig. 17 Precision of turning points*

Therefore, the ANN could predict turning point with different precision in narrow channel or open seas. The precision could be increase by adjusting parameter ε.

# 10 Conclusions

The proposed prediction model by using DBSCAN algorithm and Artificial Neural Network can prove the effectiveness to predict marine traffic. This model could be used for early warning and guidance system before any dangerous situations occurs. As in this study; data file of the vessel has been updated and Neural Networks have been trained in 180 seconds sampling period and then turning points predicted with trained Neural Network.

As another possible way to use such proposed model for marine traffic and environmental conditions. Moreover, such proposed model could be used for any specific vessel to predict her movement.

The prediction performance was found to be successful on the turning regions. Route prediction is shown in Fig 20 and Fig. 21.
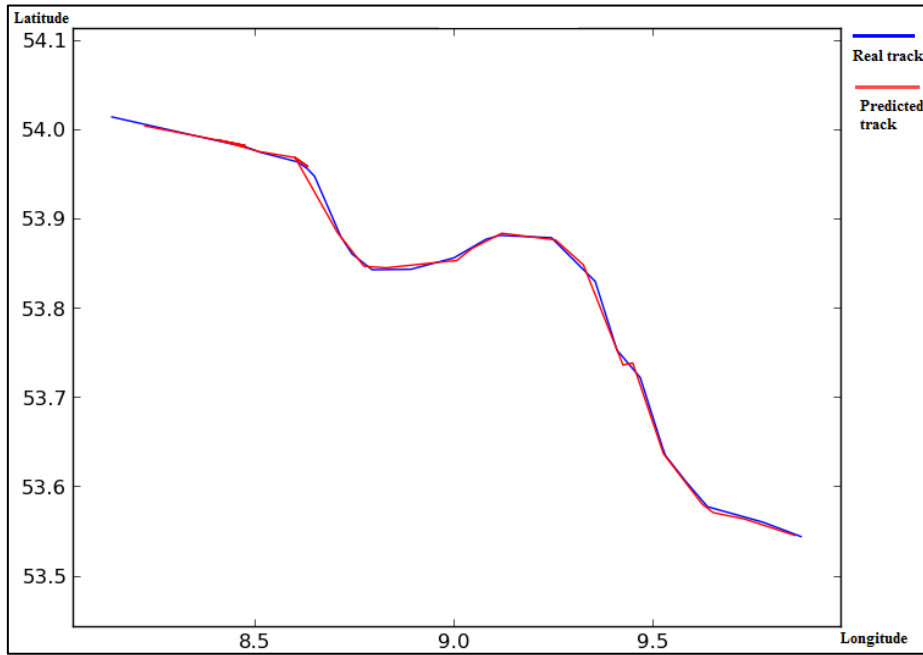
*Fig. 18 Real and predicted route of vessel for 24 hours*

Also need use all data from marine traffic because got 300,000 points, but used only 100,000. Moreover, some turning regions are the same for different ports of destination for example the route from North Baltic Sea to the North Sea will be same for all ships.
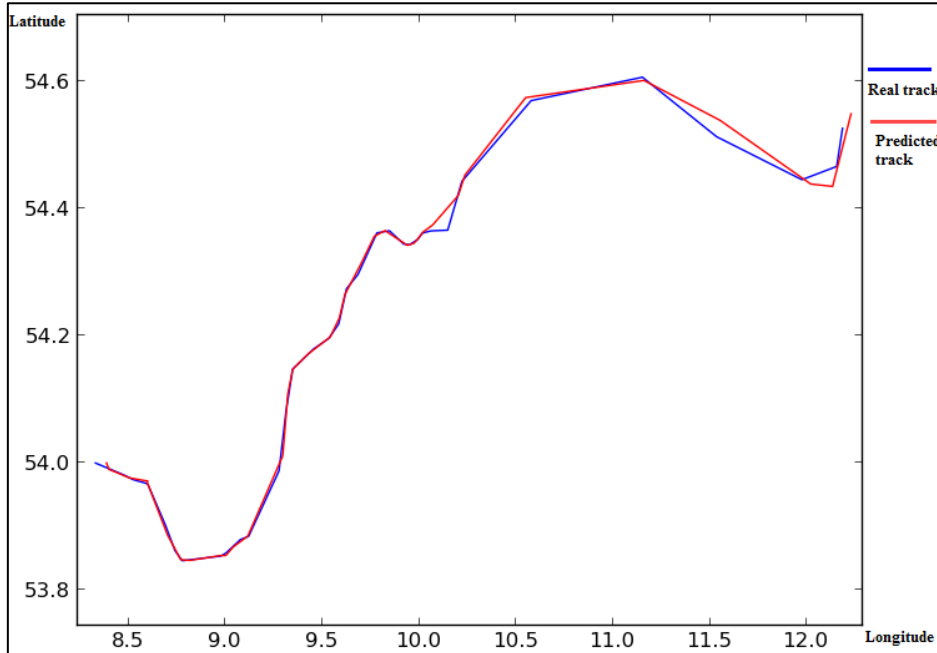


*Fig. 19 Real and predicted route of vessel for 24 hours*

The proposed model was developed and demonstrated to show its prosperous aspects. Conclusions can be drawn as follows.

1. The marine traffic prediction model is proposed and developed to demonstrate its effectiveness.
2. Marine traffic can be statistically analyzed and used for prediction.
3. The proposed model could be used for traffic flow estimation.

The proposed model can easily to predict future marine traffic situation. The system can be utilized to plan VTS and on-land AIS stations and to assess the influence of various waterway-area development projects.

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