A Novel Approach towards Gap Filling of High-Frequency Radar Time-series Data

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Keywords: Time-series Analysis, Deep Learning, Machine Learning, Gap Filling, High Frequency Radar.

Abstract: The real-time monitoring of the coastal and marine environment is vital for various reasons including oil spill detection and maritime security amongst others. Systems such as High Frequency Radar (HFR) networks are able to record sea surface currents in real-time. Unfortunately, such systems can suffer from malfunctions caused by extreme weather conditions or frequency interference, thus leading to a degradation in the monitoring system coverage. This results in sporadic gaps within the observation datasets. To counter this problem, the use of deep learning techniques has been investigated to perform gap-filling of the HFR data. Additional features such as remotely sensed wind data were also considered to try enhance the prediction accuracy of these models. Furthermore, look-back values between 3 and 24 hours were investigated to uncover the minimal amount of historical data required to make accurate predictions. Finally, drift in the data was also analysed, determining how often these model architectures might require re-training to keep them valid for predicting future data.

1 INTRODUCTION

The growth of the blue economy and maritime operations, and the importance given to sustainable oceans has rendered the availability of real-time oceanographic observation and forecast data to be crucial in this day and age. Such data can be used in various applications such as oil spill response, maritime security, and monitoring of the coast and marine environments amongst others (Gauci et al., 2016). Observation data can be collected via in-situ methods (e.g. buoys and floats), and also via remote sensing such as High Frequency Radars (HFR).

HFR networks consist of a number of coastal radar antennas, and the data from all the radars in the networks is aggregated together to provide real-time observations (maps) of oceanographic parameters, such as sea surface currents (Gauci et al., 2016). One such radar network is the Calypso HFR network, where the antennas are distributed along the coasts of the Maltese Islands and Southern Sicily providing real-time observations in the Malta-Sicily channel, and in waters south of the Maltese Islands.

Observation data collected from such instruments can be considered to be closer to reality than data generated from oceanographic hydrodynamical models, and can have substantial spatial coverage (albeit without providing data for different depth levels as hydrodynamic models). On the other hand, they are prone to errors. Instruments and related electronics can malfunction from time to time, and are prone to interference from other sources of radio waves at frequencies close to their operational frequencies. Such circumstances result in degraded outputs, limited spatial coverage, and the occurrence of gaps (spatial areas within the domain with missing or low quality data) (Gauci et al., 2016). These gaps obviously hinder the effectiveness of the applications that make use of this real-time data. Therefore, gap-filling techniques would be desirable to fill such gaps with data close to reality.

Over the years many have obtained reasonably accurate results using numerical techniques such as interpolation. However, techniques such as regression suffer in cases where gaps become substantial in size. Good quality prediction is a difficult task, especially for areas such as the Mediterranean Sea, due to the large temporal and spatial variability of wind and currents over this area. Therefore, more complex models such as machine learning models, and especially deep learning architectures, would be more suitable.

In this paper, we investigate the use of Artificial Intelligence (AI) techniques to perform gap-filling on

Camilleri, A., Azzopardi, J. and Gauci, A.
A Novel Approach towards Gap Filling of High-Frequency Radar Time-series Data.
DOI: 10.5220/0011540400003335
In *Proceedings of the 14th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2022) - Volume 1: KDIR*, pages 229-236
ISBN: 978-989-758-614-9; ISSN: 2184-3228

observation data collected by the Calypso HFR network. Our aim is to create an accurate, sea surface current gap-filling model which uses machine learning techniques. This aim is attained through the following research objectives:

1. Identify the best-performing machine learning model architecture;
2. Investigate the effect of external features such as satellite wind data, which can be added to the currents data to enhance the prediction quality;
3. Attempt to identify the minimal amount of look-back historical data required in order to train a gap-filling model which gives accurate results; and
4. Investigate how often the gap-filling models will require retraining, in order to keep them valid for predicting future data.

Research performed in this area generally resorts to using numerical techniques and often times simple Feed-forward neural network models (Gauci et al., 2016; Ren et al., 2018; Vieira et al., 2020). Although relatively accurate results can be obtained, this research is taken further by introducting other machine learning models, and providing a more in-depth analysis on the use of external features, look-back required, and data drift.

2 RELATED WORK

This research builds mostly on the research performed by Gauci et al., where they also performed gap-filling of the HFR sea-surface currents data in the Malta-Sicily Channel (Gauci et al., 2016). Due to the shortcomings of statistical methods, they considered using Artificial Neural Networks (ANN) models in order to fill gaps in the radar maps. The ANN models were built using previous observations of HFR data, in addition to satellite wind observations.

Ren et al. utilised different data sources to predict the coastal sea surface current velocity in the Galway Bay area (Ren et al., 2018). Three-layer Feed-Forward Neural Network (FFNN) models were trained on different coordinates independently using historical look-back data. Different experiments were carried out, using tide elevation, wind speed and direction and sea surface currents data to make predictions (Ren et al., 2018).

Finally, Karimi et al. also applied ANN models to try predict time-series sea level records for gap-filling (Karimi et al., 2013). They found that using historical data as inputs to the models gave better results, and used six previous time-steps in order to make predictions (Karimi et al., 2013).

2.1 Model Selection and Hyper-parameter Tuning

A number of different statistical techniques have been employed for this problem including interpolation and linear regression amongst others (Gauci et al., 2016; Karimi et al., 2013; Pashova et al., 2013). Machine learning models (most notably ANNs), have often been found to outperform statistical techniques.

Gauci et al. and Ren et al. both applied FFNNs to HFR data to try fill gaps in sea surface current radar maps. Experiments were carried out to determine the adequate amount of historical radar observations to use as an input to the models (Gauci et al., 2016; Ren et al., 2018). Song et al. applied multiple LSTM networks to predict sea surface height anomalies. Predictions were made for 1 day ahead, using data from (L) previous days (Song et al., 2020). RF models were utilised by Kim et al. to perform gap-filling of eddy covariance methane fluxes (Kim et al., 2020). Finally, Wolff et al. compared a number of different machine learning models to predict sea surface temperature including FFNNs, LSTMs, as well as RFs. To train the models they used historical data (Wolff et al., 2020).

2.2 Feature Selection

Gauci et al. used a combination of radar data and additional wind data and these two sources allowed them to make more intelligent predictions in order to fill gaps in the radar maps (Gauci et al., 2016). Similarly, Vieira et al. also tried experimenting by adding wind speed and direction measurements to predict gaps in the wave height (Vieira et al., 2020).

2.3 Temporal Historical Data

When dealing with time-series data, predictions can be made in one of the following ways: using a single previous time-step or multiple time-steps to make predictions. The reason for using historical data known as look-back, depends on the variation of the data in space and time (Ren et al., 2018).

Through experimentation, (Gauci et al., 2016) as well as (Mahjoobi and Adeli Mosabbeb, 2009) found that when more than six hours were used, the correlation of data observations was not strong enough (Gauci et al., 2016; Mahjoobi and Adeli Mosabbeb, 2009).

2.4 Data Drift

The concept of drift in time-series data is related to the data changing over time (Vieira et al., 2020). Using machine learning models is a good idea because they are able to learn patterns and non-linearity in the data (Vieira et al., 2020).

Gauci et al. and Pashova et al. trained their models on data collected over a couple of years, and filled in the gaps in the data within the same time range which were missing (Gauci et al., 2016; Pashova et al., 2013). Mahjoobi et al. gathered data between September and December from 2002 and 2004. The data from 2002 was used to train the models, while the data from 2004 was used to test and evaluate their models (Mahjoobi and Adeli Mosabbeb, 2009). Although different time ranges were used to train the models for gap-filling in previous research, we did not encounter previous works that investigate how often gap-filling models would require retraining when trained on specific periods of time.

3 METHODOLOGY

This section starts with a system overview, followed by a description of the data sources, and the preprocessing techniques used. Subsequently, the methodology used to achieve each objective are presented.

3.1 System Overview

As mentioned in Section 1, the problem at hand requires the filling of HFR sea surface currents for reasons such as maritime security, among others.

Interpolation techniques were investigated to achieve a baseline through filling artificially created gaps of different sizes within the data domain. Three machine learning models were considered according to the literature found: FFNN, LSTM, and RF model architectures. Hyper-parameter tuning of the model architectures was carried out to determine the best performing model. These investigations are linked to Objective 1, and discussed further in Section 3.3.2.

The addition of wind data to the input data was considered, related to Objective 2. The addition of external features for environmental data prediction is a common practice used in literature. Different experiments were carried out to achieve an optimised hyper-parameter configuration for each model architecture, discussed further in Section 3.3.3.

An investigation was carried out to determine the minimal amount of look-back time-steps used in order to make predictions, related to Objective 3. Between 3 and 24 hours of look-back were considered, discussed further in Section 3.3.4.

Drift in the data was also investigated in Section 3.3.5. This investigation was related to Objective 4, and carried out to determine how often the models would need re-training, to make predictions on future data without losing accuracy. Finally, the optimal gap-filling model configuration was used to train a model for each coordinate in the HFR map, where independent models were trained on the U and V data components.

3.2 Data Pre-processing

3.2.1 Sea Surface Current Radar Data

The HFR data used was obtained from the Calypso Professional Data Interface. HFR data between the Malta-Sicily channel is provided, which is recorded with a temporal frequency of one hour. This hourly data can be downloaded as is, or aggregated into daily files readily available for download.

The data between $01/01/2018\ T$ 00:00 GMT and $31/12/2019\ T$ 23:59 GMT was obtained in the form of hourly files, and contained the recorded HFR data for coordinates within the radar map. The data for each coordinate is recorded in the form of U and V water velocity components, which together form the sea surface current velocity matrices having dimensions ($time = 1$, $lat = 43$, $lon = 52$). The values of the longitude and latitude arrays have units 'degrees East' and 'degrees North' respectively, while the U and V velocity data is recorded in 'm/s'.

3.2.2 Additional Data

The global ocean near real-time wind velocity data was obtained from the Copernicus Marine website. The data was obtained in the same date range as the radar data, and stored in a single file. The U and V wind velocity matrices had the following structure ($time = 2920$, $lat = 25$, $lon = 25$), due to the fact that the data was recorded at a temporal frequency of six hours rather than one hour, and the data was recorded at a different spatial frequency than the HFR data.

Due to the temporal and spatial frequencies of the satellite wind data not correlating with the HFR data, pre-processing had to be carried out on the wind data. Bi-linear interpolation was applied to the U and V raster grids to up-sample the data spatially and linear interpolation was used to increase the temporal frequency of the wind data from six hours to one hour (Gauci et al., 2016).

3.2.3 Dataset Compilation

Once the datasets were pre-processed as mentioned in the two previous sections, in order to train the machine learning models, the data required compilation before being inputted into the models. The datasets were split into training, testing and validation data using k-fold cross validation. *K*-fold cross validation is a commonly used technique in machine learning for model selection (Mahjoobi and Adeli Mosabbeb, 2009). The number of folds chosen for experimentation was 10, as done by (Mahjoobi and Adeli Mosabbeb, 2009).

3.3 Implementation

3.3.1 Baseline Interpolation Techniques

When dealing with gap-filling, one of the most common simple techniques which has been used throughout literature has been interpolation, and more specifically linear interpolation (Gauci et al., 2016; Ren et al., 2018). The three interpolation techniques considered in this research were: Bi-linear, Nearest Neighbour and Inverse Distance Weighted (IDW). In order to test how efficiently these techniques could fill gaps, the notion of 'bounding boxes' was adopted.

When analysing the HFR data, it was discovered that more data is available in the centre of the domain. Therefore, a central coordinate at Longitude: 14.679° *East* (30) and Latitude: 36.421° *North* (25) was chosen and bounding boxes having sizes: 3, 5, 7, 9, 11, 13, 15 and 21 were constructed around this central coordinate.

For each available time-step in the data, the U and V matrices were processed separately. For each time-step, the values within the bounding box were set to 'Nan' values to create artificial gaps in the raster grid. The different interpolation methods were then applied to try fill the values within the bounding box. The reason increasing sizes of bounding boxes were used, was to test how accurately these statistical techniques could fill in missing data when neighbouring data is reduced.

3.3.2 Machine-learning Architecture Overview

More complex, but efficient approaches which are most commonly used for gap-filling, are machine learning models. As seen in Section 2.1, one of the most commonly used machine learning approaches for gap-filling are FFNN models (Gauci et al., 2016; Karimi et al., 2013; Pashova et al., 2013; Ren et al., 2018; Vieira et al., 2020). Other commonly used approaches are LSTM models (Song et al., 2020; Wolff et al., 2020) and RF models (Kim et al., 2020; Ren et al., 2018; Wolff et al., 2020). Therefore, these three different machine learning architectures were considered for gap-filling, in order to find the best performing model through hyper-parameter optimisation, as stated in Objective 1.

Feed-Forward Neural Network Model - FFNN models are a commonly used machine learning technique because of their simple structure. The models trained for gap-filling were 3-Layer FFNN models because these were commonly used in literature (Gauci et al., 2016; Pashova et al., 2013; Ren et al., 2018; Vieira et al., 2020), and have been known to produce satisfactory results. In this model, the sum carried out on a hidden neuron a_j is calculated as follows $a_j = \sum_i x_i w_{i,j} + b_{1,j}$, where x_i represents the input values, $w_{i,j}$ represents the weight between the input and hidden layers and $b_{1,j}$ represents the bias for the hidden layer (Vieira et al., 2020).

The size of the input layer was set according to the number of look-back time-steps considered. The look-back variable was initially set to 6, as done by (Gauci et al., 2016; Pashova et al., 2013) who applied FFNN models on oceanographic data for gap-filling. The number of neurons h_n used in the hidden layer was set to 15 neurons, and the number of epochs was set to 50, both determined through experimentation. The size of the output layer was set to 1 neuron. The ReLu activation function was applied to the input and hidden layers as done by (Wolff et al., 2020). The model was compiled using the Adam optimiser with a learning rate $\alpha = 0.001$ as done by (Sahoo et al., 2019), also determined through experimentation. Finally, the loss function chosen was the Mean Squared Error loss as done by (Sahoo et al., 2019).

Long Short-Term Memory Network Model - Although less commonly used for gap-filling, the LSTM model has been found in literature to perform better than the classic FFNN model. The LSTM model network block is composed of different gates, the input i_t, output o_t and forget f_t gates, where t represents the prediction period (Sahoo et al., 2019). One or more hidden layers were used with h_{in} neurons in each layer i, as done by (Wolff et al., 2020). Similar to the FFNN implementation, the look-back variable was used to define the input layer size, initially set to 6 and the output layer was also set to 1. The size of the hidden layer was set to 30 neurons and the number of epochs used was set to 50, both determined through hyper-parameter tuning. Finally, the model was compiled using the same optimiser, loss function and activation function applied to the FFNN model.

Random Forest Model - RF is not as commonly used in literature for gap filling as the FFNN and LSTM models, it has been used due its simplicity and relatively good performance, as advised by (Kim et al., 2020; Wolff et al., 2020).

Among the different parameters the RF model accepts, the 'n_estimators' and Boolean 'bootstrap' variables were inputted into the model. The 'n_estimators' variable represents the number of trees to build in the RF, set to 50, while the 'bootstrap' Boolean variable determines if bootstrapping is used or not. Bootstrapping is a process whereby, a random sample from the original dataset is selected at random with replacement when training each tree. This helps with reducing over-fitting within the model, and was therefore set to 'True'. These hyper-parameters were determined through experimentation.

3.3.3 Feature Selection

Environmental data such as the sea surface currents could be effected by external features such as wind, tides and waves amongst others. Some researchers which included the use of additional features in their prediction models were (Gauci et al., 2016; Mahjoobi and Adeli Mosabbeb, 2009; Ren et al., 2018; Vieira et al., 2020; Wolff et al., 2020). The addition of external features was investigated in relation to Objective 2.

The input data for a particular time-step contained 6 hours of HFR data concatenated with 6 hours of wind velocity data. After adding wind velocity as features, the best performing FFNN model was found (by experimentation) to have 25 neurons in the hidden layers. The models in this phase were trained using the same optimiser function, loss function, activation function and number of epochs as described in Section 3.3.2. The input layer now contained 12 neurons as look-back observations (Gauci et al., 2016).

The LSTM model experiments carried out (after adding the wind data) were similar to those carried out on the FFNN model. The model architecture found to produce the best results used 30 neurons in the hidden layer. As done for the FFNN model, 12 neurons were used in the input layer.

On the other hand, since the RF model did not require excessive hyper-parameter tuning, only a few experiments were carried out on it. The models used for these experiments were built using bootstrapping and utilising 50 trees, since these were the best performing hyper-parameters found.

3.3.4 Temporal Historical Data

The notion of a look-back variable was used to determine the ideal minimum amount of historical time-steps required in order to accurately predict the HFR data, stated in Objective 3.

The look-back values taken into consideration were: 3, 12, 18 and 24 hours, as the experiments carried out for a look-back of 6 hours have already been discussed in Section 3.3.2. For the FFNN model, experiments on the different look-back values were carried out using the same optimiser function, loss function, activation function and number of epochs used in Section 3.3.2. The models were built using 15 in the hidden layer, determined through experimentation.

For the LSTM model architecture, the same look-back values used for the FFNN model were considered. For the look-back value of 3 hours, 20 neurons were used in the hidden layer. For the look-back values of 12 and 18 hours, 50 neurons were used and for 24 hours, 52 neurons were found to produce the best results.

For the RF model, the different look-back experiments carried out used bootstrapping in order to train the models. The experiments carried out on each of the look-back values used 50 trees to build the models respectively, determined through experimentation.

3.3.5 Data Drift

When dealing with environmental data such as sea surface currents data which is constantly changing with time, prediction models might need re-training to be able to predict data further away in the future. Therefore, an investigation was carried out by training the different model architectures on data spanning over different time ranges, related to Objective 4.

The experimentation carried out in order to investigate if there was any drift in the data was done by splitting the 2018-2019 radar data into partitions. The first partition entailed the full two year dataset, while the remaining partitions split the data into subsequent 6 month ranges. Then, the HFR data was obtained from January to March of 2020, and used to evaluate the models. Data from 2020 was used as this data was unseen future data. The look-back value used for these experiments was set to 6 hours, determined to be an appropriate minimal amount of historical data to use in Section 3.3.4.

3.3.6 Gap-filling System Overview

The final step for the research carried out on the gap-filling, was to use the best performing machine learning prediction model with optimised hyper-parameters, to train a model for the U and V HFR data for each coordinate in the domain containing available data. This was done by loading the required data between 2018 and 2019, pre-processing the data to obtain the x and y data according to the look-back value selected and shuffling the data randomly to avoid bias in the models. Data from 2020 was then considered for gap-filling prediction.

In order to make predictions, for the look-back values of the first prediction time-frame, the missing U and V values were filled using the bi-linear interpolation method. This was done since, in order to make a prediction for a particular coordinate, each look-back time-step required available HFR observations. Bi-linear interpolation was chosen as it performed best when compared to other interpolation techniques.

4 EVALUATION

The error metric used to evaluate the models was the Mean Squared Error (MSE), used by Wolff et al. (Wolff et al., 2020).

4.1 Model Selection

As mentioned in Section 3.3.2, initial experimentation on the different machine learning models was carried out using a look-back of six hours, as this value was found to be appropriate to make accurate predictions in literature (Gauci et al., 2016; Mahjoobi and Adeli Mosabbeb, 2009; Pashova et al., 2013).

4.1.1 Interpolation vs Machine Learning Models

The Bi-linear interpolation method was found to be the best performing interpolation technique. When comparing the machine learning models to the interpolation techniques, it was discovered that as the size of the gap in the raster grid grew, the interpolation techniques did not manage to fill the gaps as well as the machine learning models. The results achieved by the machine learning models were found to be significantly better than those generated by simple interpolation methods.

4.1.2 Machine Learning Model Comparison

Experiments were run on six selected coordinates in the domain, for each machine learning model architecture using the best configurations discovered from the hyper-parameter tuning carried out. The results of the experiments carried out are presented in Tables 1 and 2. The results depict the averaged MSE over the test data for the U and V component data, trained on each of the machine learning models (for independent coordinates in the raster grid).

When comparing the results, the LSTM model was found to perform statistically better than the FFNN and RF models, followed by the FFNN model. Although the RF performed quite well, it did not manage to exceed the neural network model architectures.

4.2 Feature Selection

As an extension of the experiments carried out on the three machine learning models, additional data was also considered. The results from each model architecture using both wind and radar data, were statistically tested against the model configurations not using the additional wind data. This was done to investigate if adding the wind data to the HFR data, would improve predictions, related to Objective 2.

For all three model architectures, although the addition of the wind data improved the prediction results very slightly for some coordinates, the improvements were very minor. This meant that accurate predictions could still be made when only taking into consideration the HFR sea surface currents data in order to fill gaps, as the difference in the MSE results was almost negligible. Table 3 depicts the results obtained when using the LSTM model.

4.3 Temporal Historical Data

An investigation was carried out in relation to the different amount of historical look-back data to use. The minimum amount of look-back was desired since, when making predictions to fill gaps in the data for a time-step, the previous consecutive look-back values must all be available. This experimentation was done as an extension of the experiments carried out using a look-back value of six hours, presented in Section 4.1, related to Objective 3.

Figure 1 depicts the average MSE results obtained from each of the look-back experiments carried out on the LSTM model. Although using longer look-back sequences produced slightly better results overall, the more look-back is used, the more training data would be required in order to train these models, as mentioned previously. Therefore, using a look-back of six was found to be an appropriate minimal amount of historical data to use when training the different model architectures.

4.4 Data Drift

Experimentation was carried out on the HFR data used to train and test the neural network model architectures, in order to investigate any potential drift in the data, related to Objective 4. The model architectures used were the hyper-parameter tuned architectures discovered through experimentation carried out in Section 3.3.2.

Figure 2 depicts the experiment results on the LSTM model. When comparing the results obtained, no drift was detected in the data. The experiment

Table 1: Averaged Validation MSE for U Vector Data.

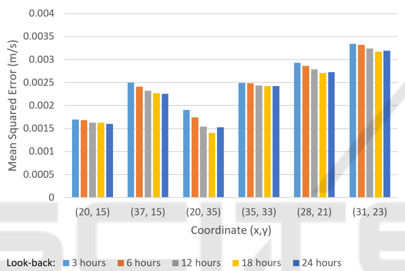
	Coordinate					
Model	(20, 15)	(37, 15)	(20, 35)	35, 33)	(28, 21)	(31, 23)
FFNN	0.00176	0.00246	0.00153	0.00252	0.00297	0.00335
LSTM	**0.00168**	**0.00241**	**0.00174**	**0.00249**	**0.00286**	**0.00332**
RF	0.00186	0.00266	0.00148	0.00279	0.00319	0.00360

Table 2: Averaged Validation MSE for V Vector Data.

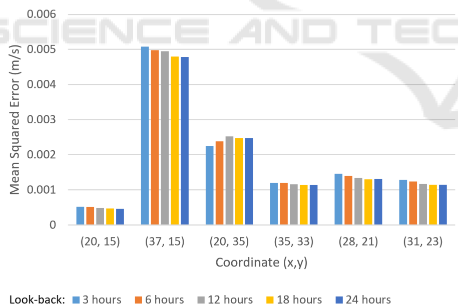
	Coordinate					
Model	(20, 15)	(37, 15)	(20, 35)	35, 33)	(28, 21)	(31, 23)
FFNN	0.000520	0.00508	0.00261	0.00119	0.00144	0.00124
LSTM	**0.000509**	**0.00498**	**0.00238**	**0.00120**	**0.00141**	**0.00124**
RF	0.000562	0.00559	0.00247	0.00129	0.00152	0.00137

Table 3: LSTM Feature Selection Model Averaged Validation MSE.

	Coordinate					
Data	(20, 15)	(37, 15)	(20, 35)	35, 33)	(28, 21)	(31, 23)
U	0.00167	0.00240	0.00230	0.00246	0.00283	0.00325
V	0.000506	0.00500	0.00240	0.00118	0.00140	0.00122

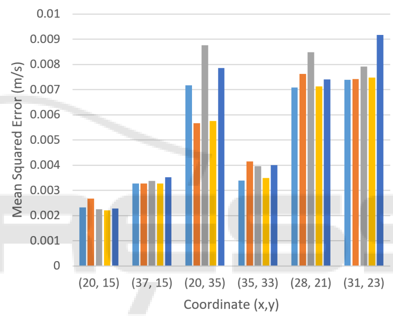


(a) U Data MSE Results.

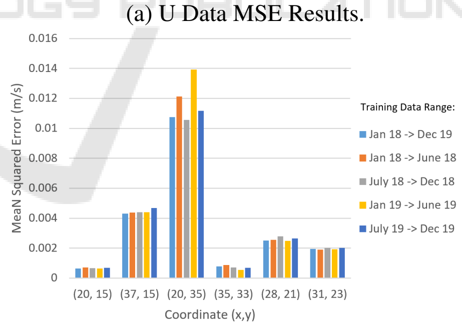


(b) V Data MSE Results.

Figure 1: LSTM Look-Back Comparison Results.



(a) U Data MSE Results.



(b) V Data MSE Results.

Figure 2: LSTM Data Drift Experiment Results.

using all data between 01/2018 and 12/2019 was selected as the most appropriate amount of data in order to train the models since, using all the data rather than just a 6 month partition, performed slightly better for most coordinates overall.

4.5 Gap-filling System Overview

The LSTM model configuration having the following architecture (6:30:1), obtained improved results over the other models. This configuration was used to train different models on the U and V component HFR data between 2018 and 2019, for all coordinates in the raster grid. Figure 3 depicts the gap-filling carried out on data in July 2020. As can be seen from the map plot, the prediction models manage to learn trends in the data domain, such as the eddy currents. When investigating the difference between the actual and predicted vector values, the differences were always less than 1m/s which shows that the predictions were very accurate.

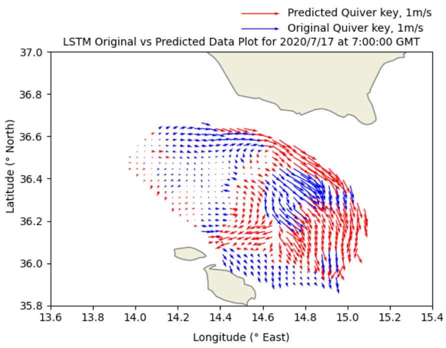


Figure 3: LSTM Gap-Filling Hybrid Model Predictions.

5 CONCLUSION AND FUTURE WORK

The aim of this research is concerned with achieving accurate gap-filling of the HFR sea surface current data through Objectives 1-4. It was discovered that interpolation techniques are not be as accurate as using machine learning models (Gauci et al., 2016). Furthermore, when comparing the three machine learning models, the LSTM model was found to be the most effective.

Furthermore, the addition of external satellite wind data to the training data did not improve the results significantly, as discovered by (Vieira et al., 2020). An investigation was also carried out on the amount of look-back historical data to use in order to train the models. Through the experimentation carried out, it was found that using a look-back of six hours made more sense due to the constraints of the dataset, as done by (Gauci et al., 2016).

Finally, an investigation was carried out related to how often the gap-filling models would require retraining in order to keep them valid for predicting future data. It was found that there was no drift in the data when being trained on certain periods. Furthermore, training the models on the full two years achieved the best results over-all and was able to make accurate predictions on data in 2020.

5.1 Future Work

Although the wind velocity did not improve the prediction results for gap-filling of the sampled data, other external features could also be investigated further. Tidal elevation and sea surface heights could be investigated with regards to their effects on the HFR sea surface current data.

Further investigations on the possibilities of seasonal drift could be investigated further. Models could be trained on data from different seasons to test whether any trends in the data are found, and if models trained per season could achieve more accurate predictions. Finally, this research can be taken further to achieve short-term forecasting of the HFR data, which is already in the works.

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