PhD project plan - Exploiting data to support operations of EXPOSED aquaculture installations

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1 Introduction

Aquaculture is an increasingly important industrial sector in Norway. The Norwegian Ministry of Fishery and Aquaculture states that its a long term goal for aquaculture is a five fold increase in production by 2050 [1]. This stands in direct contrast with recent Norwegian news[2] which states that aquaculture in Norway is facing a growing challenge with regards to fish disease and environmental impact.

To help the industry reach the goal set by the Ministry of Fishery and Aquaculture of a five fold increase - without increasing the environmental impact - we need to increase the amount of locations suitable for modern aquaculture development. The SFI project EXPOSED[3] is trying to do this by researching and developing technologies that enable aquaculture to operate at more exposed (offshore and subject to harsh weather) locations.

A part of the technology needed for this is increased level of monitoring and decision support. Making use of the increasing amount of data gathered on these aquaculture installations to automate and support personnel would decrease cost and the amount of hours spent on the installations thus decreasing the risk for the personnel at these more exposed locations. Decision support systems within aquaculture traditionally employ numerical models (e.g. [7]). With the increasing amount of data being gathered at these installations, using machine learning to create models from the data would be a great addition to these models as a part of a decision support system.

Machine learning is a promising field of research. Most recently shown by the rising field of deep learning. Deep Learning has been employed for data analysis within different domains, including, but not limited to; speech recognition [5, 10], object recognition [4] and text processing [2]. Recently it has also been tried as methods for improving computer-chess[4] and computer-go [12]

Given enough data and targeted at the correct problems (e.g. where learning patterns across huge amounts of data will lead to a solution) these methods excel. However if the data is sparse these methods can be hard to utilize. Another missing feature from these types of methods is explainability.

Methods like deep learning (and other sub-symbolic methods) are not easily explained. It can be done through analyzing activation patterns in the neural networks etc, but it is undecipherable to anyone but experts in the field.

Explainability is a key factor in making the human operator trust the decision/operator support system and other machine learning methods are easier to explain and understand, such as Bayesian networks[15] or to a lesser degree Evolutionary Algorithms[11, 6].

Case-based reasoning (CBR)[1] is an example of another method that is based on symbols and knowledge (also known as a knowledge-based reasoning method). As the method is heavily inspired by cognitive models, the method is more easily explainable. CBR in combination with knowledge engineering in cooperation with human experts can even achieve high performance without the

[1] http://www.vg.no/nyheter/innenriks/naeringsliv/slik-kan-fremtidens-lakseoppdrett-se-ut/a/23568283/

[2] http://www.vg.no/nyheter/innenriks/her-er-kartet-som-faar-ekspertene-til-aa-slaa-laksealarm/a/23598279/

[3] http://exposedaquaculture.no/

[4] http://erikbern.com/?p=841

presence of large data-sets. The method has been tested with success in several domains such as oil & gas[8] and fish farms [16]. This method is typically less dependent on a large data corpus than other methods such as neural networks. This property enables us to use CBR as a method for predicting rare events.

To reach the goals set for the SFI project: improved quality, safety and efficiency in exposed fish farming operations - the solution should utilize the strength of all of these methods. E.g. deep neural networks may be used to detect anomalies which correlates or causes a change in site state which may be extracted and refined as a case and stored in a case-base. This could then be used by a CBR system to predict future anomalies with a greater ability to explain how it came to this conclusion.

Machine learning has already been applied to fisheries and aquaculture through decision support, examples of this is; Operational support in fish farming through using CBR[16], decision support model for fisheries management in Hawaii[13], decision support system for fish disease/health management[17], decision support for sustainability[9]. Our work will build on these results, applying what has been learned in previous studies. Decision support systems within aquaculture has been used but a predominant part of the decision support systems described in literature[3, 7] only employ user input and numerical models. Our system will employ data-based machine learning methods that build models and tries to predict future states, knowledge based methods that improves explainability and can support prediction of rare events, all in addition to the traditional numerical models.

The goals of this PhD project is to contribute to a subset of the main goals set for the SFI-center as mentioned above -

Goal ($G1$) : *This PhD project will study AI methods aiming for safe and sustainable fish production at exposed aquaculture sites through utilization of sensor data as well as human experiences to develop and test a system for monitoring, prediction, and operational decision support.)*

2 Objectives

The work done in this project will contribute to machine learning and artificial intelligence via testing the applicability and performance of AI/ML methods in the aquaculture domain. On the other side, the project will advance decision support systems within the aquaculture domain via testing how ML methods can increase their performance and usefulness. However many of today's popular machine learning methods requires large databases of instances to be trained properly, but many of the events that operators wants to avoid on a installation are rare and as such the data about them is sparse. More specifically the measurable academic objectives of this PhD project is:

1. Establish the current state of the art in terms of decision support systems within aquaculture and the role of machine learning in these decision support systems.
2. Create and test machine learning methods that uses data from aquaculture installations and contributes to a decision support system for such a site. Typically these methods will try predict future states of a aquaculture installation and this prediction can be used by a decision support system.
3. Create and test knowledge-based methods such as CBR for detecting and predicting rare events in the aquaculture domain.

3 State of the PhD project

The EXPOSED SFI project is currently gathering sensor data and operational data from exposed sites. Table 1 lists some of the data gathered from the pilot sites in the EXPOSED project.

Environmental measurements	Installation	Production data
Wind (max and avg)	Movement (accelleration)	Fish mortality
Waves (max and avg)	Anchor load	Fish grouping
Current (direction and speed at 3 depths)	Operational status[5]	Feeding
Temperature	-	-

Table 1: Table listing some of the data parameters gathered from sites included in the SFI EXPOSED project.

Not all of this data is gathered for every aquaculture site included in the project. As a result some sites will have more data parameters gathered than others. In addition the instrumentation of these sites are a central part of the project as such, and is thus evolving, increasing the amount data gathered at each site. At this point in the project we are focusing on implementing a prototype framework for automatically importing these data streams. As a part of this framework we implemented a way to easily test different machine learning methods w.r.t. using the different data parameters to predict future states of a aquaculture site. We have performed two tests in this regard which we present in the following subsection.

3.1 Predicting installation movement

In this experiment we tried to predict the movement of an aquaculture cage structure based on wind data gathered from a buoy that is situated close (within 100m) of the cage. To approximate the level of movement on the cage structure we calculated the variation of the x axis of the accelerometer mounted on the cage structure over the span of an hour (36000 data points, 10 hz). The prediction was made with a neural network with inputs being Wind Direction, Wind Gust and Wind Speed. The output of the neural network is the predicted movement. The network could only see the current time series data (not any history). Figure 1 show the accuracy of this prediction.

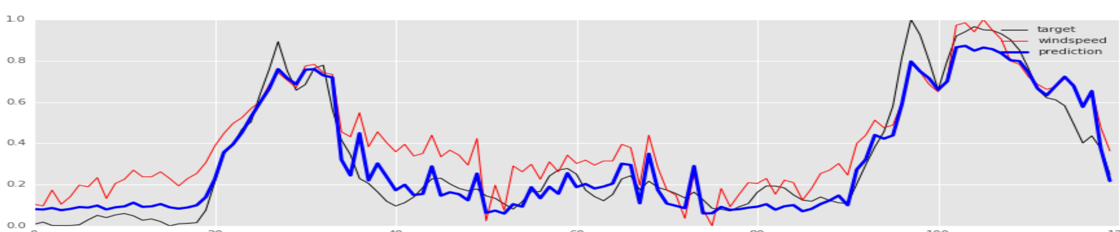

Fig. 1: A graph showing a neural network predicting (blue line) the variation on the x axis of an accellerometer mounted on the aquaculture cage(shown as “target” or a black line in the graph). The red line depicts the wind speed.

As one can see from the figure the network predicts the movement quite precisely, however the wind speed is also highly correlated with the movement of the structure (as can be expected). Thus the neural networks net gain over wind speed is not relatively big, however it adds precision.

3.2 Predicting anchor load

In this experiment we tried to predict the load on the anchors of an aquaculture cage structure based on environmental data gathered from a buoy that is situated close (within 100m) of the

[5] This is a report of which operations could not be performed that day due to unfavourable conditions

cage. The target prediction value is the anchor load in newtons. The prediction was made with a neural network with inputs being 15 data points: current direction and speed at 3 depths, max wind speed, average wind speed, wind direction, significant wave height, wave direction and temperature. The output of the neural network is the predicted load. In the previous experiment the neural network could only see the current data at the current point in the time series. In this experiment the neural network could see the current data as well as the three previous time series points, making it a total of $4 * 15 = 60$ inputs to the neural network. Figure 2 show the accuracy of this prediction.

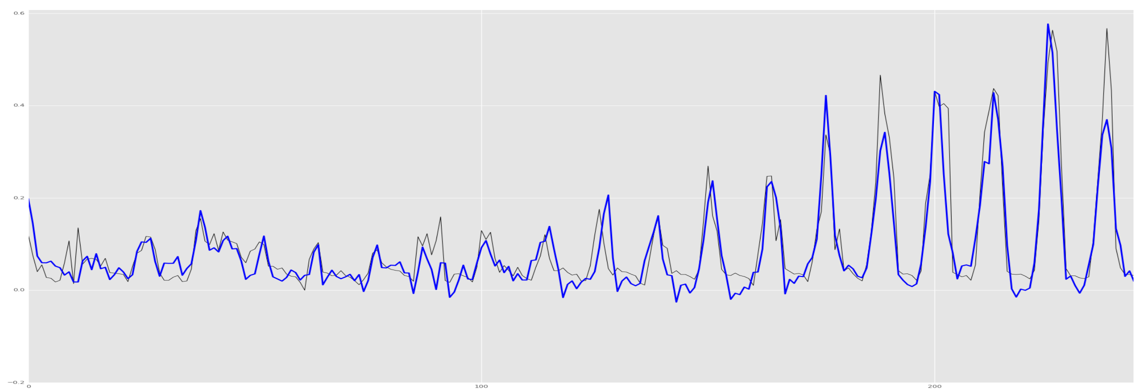

Fig. 2: A graph showing a neural network predicting the anchor load of a aquaculture cage. The blue line depicts the prediction. The black line depicts the actual load.

4 Project plan

In addition to the data listed in Table 1 the project has received a dataset describing the movements of maritime vessels in and out proximity to the aquaculture installations. We have currently combined this with a dataset describing the level of exposure to the environment for each of these sites. In addition we have added weather (wind, waves, temperature, precipitation etc) for each of the events at the relevant sites. The plan is to pick a specific type of boat fishfeed carriers, and then using the time spent at each location to classify whether or not the fishfeed loading operation was successful. We can then use the dataset to try to predict wether such a operation will be successful given the level of exposure and weather forecast. Ideally we would like to use an automated method (likely a ML method) to extract some archetype cases to add to a case-base. This case base could then be employed by a CBR as a part of a decision support system that would be more in line with the type of experience based learning they currently use in the domain.

4.1 Applying CBR

As mentioned earlier we want to apply CBR as the main interface to the user of his DSS. This is because CBR provides a good analogy for the way that this industry learns (experience based learning as opposed to formal learning), and also because CBR is well suited for situations where the data contains instances that are few but have high signal to noise ratio (archetypes); e.g. “Predicted weather conditions are very similar (90%) to a situations where the planned operation failed due to weather conditions.” Detecting such these rare instances can most easily be done with using expert knowledge (for verification) and machine learning (for finding previous situations where conditions where far from the average) in tandem. These instances can then be formed into cases where recorded result is shown along with expert input on how to achieve the best result given the conditions (could also be to abort the operation).

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