Reinforcement Learning based Production Planning in the Aquaculture Industry

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***Abstract*— Production planning and decision-making processes in the aquaculture industry are becoming increasingly complex. Decision-makers must take into consideration a large number of factors - economic, biological, environmental, etc. - and, in addition, the increasing size of enterprises and intensive production systems have exponentially increased the number of decisions to be made. The aim of this article is to evaluate the possibilities of applying a novel technique, such as reinforcement learning, to decision-making processes in aquaculture. To this end, its application in comparable industries, also part of the agricultural sector, that are more technologically advanced, is reviewed in order to use them as a reference in the short and medium term. As can be observed in this article, reinforcement learning not only offers an interesting alternative for dealing with this complexity but also makes it possible to tackle problems that had not been solved until now.**

Keywords: *Reinforcement Learning, Aquaculture industry, Decision-making.*

I. Introduction

The aquaculture production has experienced a notable increase, matching that of fishing, and has been recognized by the Food and Agriculture Organization of the United Nations (FAO) as an economic activity capable of ensuring the sustainability of Fishing resources. However, the rapid growth of productivity has generated greater complexity in the management of aquaculture companies, which is affected by various biological, technical, environmental, economic, and market factors, many of which are beyond the control of managers (Luna et al., 2019).

Over the past decades, scientific researchers and experts in R&D have developed management tools to address the needs of producers for automating and optimizing numerous strategic and operational decisions. These tools provide expert information in an accessible manner to end users and, thanks to the technological advances in Big Data and Artificial Intelligence, it has been possible to improve the ability of aquaculture companies to make decisions and develop control systems (Zhou et al., 2018). In this sense, an extensive analysis of the main business decisions has been carried out in various operational research studies, such as scheduling (Luna et al., 2020), site selection (Stagnitti, 1997), planning and facility design (Ernst et al., 2000) and hatchery management (Schulstad, 1997).

However, certain aspects have generated the need for new, more advanced technological developments in the industry. In this regard, it is important to highlight that aquaculture, especially in terms of production processes and markets, is influenced by a multitude of variables that are difficult for humans to control. These variables include biological aspects, such as growth and mortality, as well as economic aspects, such as price volatility and rising costs, and environmental aspects, such as water temperature, pollution, and weather events. In addition, the process of intensification and sustainable expansion of aquaculture in recent years has considerably increased the complexity of the industry, due to the increase in the size of companies and more intensive production. Similarly, institutional regulations are increasingly rigorous with regard to environmental aspects, increasing the management complexity.

All this demands much more efficient computational systems capable of achieving optimal results, which can be developed using Reinforcement learning (RL). As described by (Chen et al., 2021), RL is a type of machine learning that utilizes rewards acquired through interaction with the environment to shape behavior and continuously develop a strategy to maximize cumulative rewards. It is particularly well-suited for decision-making processes that adhere to the Markov property (Sutton and Barto, 2018). Deep Q-learning network (DQN), a subfield of RL, combines the powerful perception capabilities of deep learning with its own decision-making abilities (Mnih et al., 2013) offering innovative solutions to cognitive decision-making challenges in intricate scenarios.

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The objective of this study is to evaluate the possibilities of applying an innovative technique, reinforcement learning (RL), in decision-making processes in aquaculture. Much of the advances in aquaculture have traditionally been based on experience gained in other primary sector activities, such as agriculture or forestry, in order to improve the efficiency and profitability of industrial-scale aquaculture (Bjørndal et al., 2004). Therefore, we will use as a reference the literature on RL application to other agricultural activities. To this end, we will collect, review and compare all the existing publications in the in particular the Web of Science Core Collection database.

II. MATERIALS AND METHODS

In this study, we follow a three-step process that starts with the bibliographic data collection process, continues with an automatic bibliometric and mapping analysis, and ends with an in-depth traditional review of a selected number of publications.

A. Data Collection.

The most important step of a review is to find a representative sample of documents. In this regard, we accessed the ISI Web of Knowledge, in particular the Web of Science Core Collection database, with the objective of collecting all existing publications up to June 2023 that study the application of Reinforcement Learning in agriculture first, and the in the aquaculture industry.

To this end, we initially limited the search process to the documents including the term "Reinforcement Learning" and "Agriculture" in any field. Then, as that search query returned an overly diverse and poorly targeted sample, we added the requirement that the results need to be "Articles" from journals listed in the "Web of Science Index: SCI_EXPANDED". This process led us to a sample of 157 documents, which was designed to be representative of the research on reinforcement learning in agriculture.

After that, as we wanted to focus the analysis on the aquaculture industry, we repeated that search indicating the term "aquaculture" in the place of "agriculture". This led us to a sample of just 6 papers.

B. Mapping and Bibliometric Analysis.

Once we collect a representative set of documents, we, in brief, utilize bibliometric techniques to analyze the whole set and transform it into a subset that allows conducting a traditional review.

This way, we used both evaluative and relational techniques to group the existing publications in clusters, based on their aim and methods applied. In particular, we analyzed the abstract of each publication using both the Non-negative Matrix Factorization (NMF) technique in Python and the co-occurrence map provided by VOSviewer. Both techniques are described in (Baraibar-Diez et al., 2020) and have already proven their ability to identify the main research areas by which the analyzed papers are divided and capture their objectives.

C. Systematic Review.

Finally, we conduct a classical systematic review of those articles that were identified and classified in the group of "decision-making" in agriculture. Furthermore, we compare them with the sample of articles publish in aquaculture, highlighting different areas of research for the future.

III. RESULTS

A. Summary of the Data Collected.

With respect to the sample of 157 papers addressing Reinforcement Learning in agriculture, although we found studies from before the 2000s, Figure 1 shows that the research on this topic mainly started in 2015 and its now exploding in popularity.

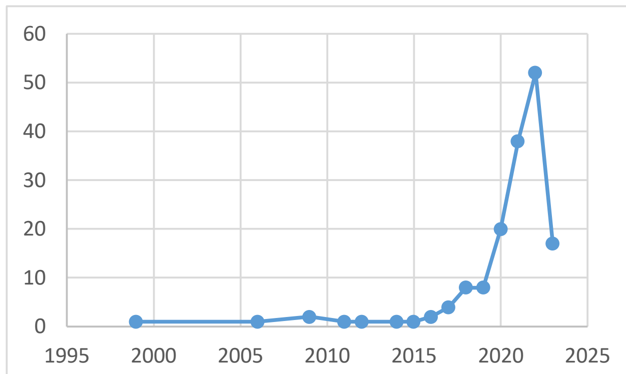

Fig 1. Evolution of the number of publications on this topic

Regarding the country of origin, most papers were written by authors from China and the USA, followed by India, Japan and England (see Table 1).

Country	Number of publications
China	78
USA	36
India	13
Japan	13
England	11
South Korea	7
Spain	7
Autralia	5
Netherlands	5
Pakistan	5

Table 1. Geographic distribution of publications on this topic (>5)

The most prolific journals—i.e., those with the highest number of publications— are Computers and Electronics in Agriculture, IEEE Access and Sensors, followed by a large number of journals with 5, 4 and 3 publications (Table 2).

Journal	Publications
Computers and Electronics in Agriculture	7
IEEE Access	7
Sensors	7
IEEE Internet of Things Journal	5
IEEE Transactions on Intelligent Transportation Systems	5
Agriculture Basel	5

Table 2. Rank order of the most influential journals by number of publications (>3)

Regarding the most influential authors, we selected 7 out of those that have publish 2 papers or more (table 3).

Author	Publications
P.m., Durai Raj Vincent	3
Elavarasan, Dhivya	3
Mohammed, Mazin Abed	3
Li, Yanfei	3
Begoña Garcia-Zapirain	2
Matt Taylor	2
Kai, Zhou	2

Table 3. Authors with at least two publications

With respect to aquaculture, the total sample of articles is presented in table 4. As can be seen, there are only a few articles applying RL in aquaculture and most of them have been published in the last few months.

Author(s)	Title	Journal
Chahid, et al. (2022)	Fish growth trajectory tracking using Q-learning in precision aquaculture	Aquaculture
Sung, et al. (2023)	Designing Aquaculture Monitoring System Based on Data Fusion through Deep Reinforcement Learning (DRL)	Electronics
Tu & Juang (2023)	UAV Path Planning and Obstacle Avoidance Based on Reinforcement Learning in 3D Environments	Actuators
Wang, et al. (2022)	Modeling collective motion for fish schooling via multi-agent reinforcement learning	Ecological Modelling
Gambin, et al. (2021)	Sustainable Marine Ecosystems: Deep Learning for Water Quality Assessment and Forecasting	IEEE Access

Table 4. Publications of RL for the aquaculture industry.

B. Mapping RL in agriculture

As already explained, we analyzed the abstract of each publication using both the Non-negative Matrix Factorization (NMF) technique in Python (Table 5) and the co-occurrence map provided by VOSviewer (Figure 2).

Both processes led us to analogous results, so it is possible to conclude that there are three main topics or research areas:

I. A first topic focused on the technical requirements of RL to be applied to agriculture;

II. a second cluster applying RL to IoT, sensors and robots working in the industry; and

III. a smaller third cluster that is specifically focused on decision-making (scheduling, planning, etc.) in agriculture using RL.

Clusters	N	Co-Words
Computational and technical requirements	72	Energy, network, datum, model, resource, edge, computing, device, learning, application, time, service, allocation, user, power
Controlling sensors and vehicles	65	Control, path, policy, robot, method, environment, learning, problem, planning, navigation, vehicle, reinforcement, time, action, function
Decision-Making	19	Irrigation, water, agent, model, uncertainty, canal, scheduling, approach, crop, learning, weather, yield, agriculture, reinforcement, parameter

Table 5. Co-words obtained in each cluster by NMF

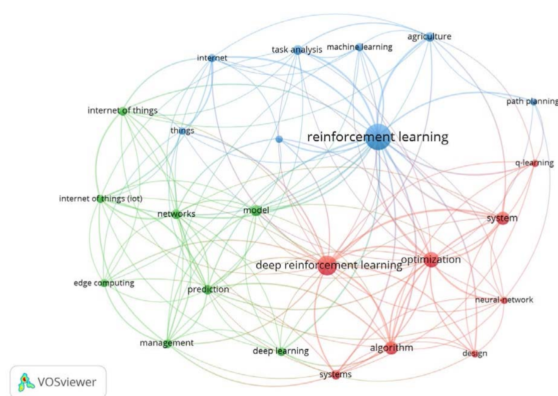

Figure 2. Most relevant words used in publications on RL in agriculture, with a minimum number of occurrences of a term of 5.

This classification is meaningful with the practice of the industry and the application of new technologies. Moreover, it is very useful for the aim of the article as it allows us to focus on those aspects related to control and, especially, decision-making.

C. *Lessons for the aquaculture industry from literature on "decision-making in agriculture using RL".*

From the results in Table 5, we started an in-depth analysis of the papers belonging to clusters 2 and, especially, 3. The following tables shows the most cited papers.

As can be seen in Table 6, the second cluster, which we called "Controlling, sensors and vehicles", is made up of articles belonging mostly to technological journals, such as Computers and electronics in agriculture.

Author(s)	Title	Journal
Ullah, et al. (2020)	Cognition in UAV-Aided 5G and Beyond Communications: A Survey	IEEE Transactions on Cognitive Communications and Networking
Samejima & Omori (1999)	Adaptive internal state space construction method for Reinforcement learning of a real-world agent	Neural Networks
Lin, et al. (2021)	Collision-free path planning for a guava-harvesting robot based on recurrent deep reinforcement learning	Computers and Electronics in Agriculture
Chen, et al. (2021)	Effective Management for Blockchain-Based Agri-Food Supply Chains Using Deep Reinforcement Learning	IEEE Access
Zhang, et al. (2019)	Double-DQN based path smoothing and tracking control method for robotic vehicle navigation	Computers and Electronics in Agriculture

Table 6. Most cited Publications - Cluster 2

The third cluster, which we called "Decision-making", consists of papers attempting to improve or optimize the results of decision-making processes, such as planning or scheduling tasks. These articles are most often found in production and management journals, although many of them are also published in technological journals (Table 7).

Author(s)	Title	Journal
Bu & Wang (2019)	A smart agriculture IoT system based on deep reinforcement learning	Future Generation Computer Systems-The International Journal of Escience
Elavarasan & Vincent (2020)	Crop Yield Prediction Using Deep Reinforcement Learning Model for Sustainable Agrarian Applications	IEEE Access
Yu & Ram (2006)	Bio-inspired scheduling for dynamic job shops with flexible routing and sequence-dependent setups	International Journal of Production Research
Elavarasan & Vincent (2021)	A reinforced random forest model for enhanced crop yield prediction by integrating agrarian parameters	Journal of Ambient Intelligence and Humanized Computing
Chen, et al. (2021)	A reinforcement learning approach to irrigation decision-making for rice using weather forecasts	Agricultural Water Management

Table 7. Most cited Publications - Cluster 2

Comparing these publications with those from the aquaculture sample, Reinforcement learning (RL) offers several opportunities to the aquaculture industry. In particular, aquaculture production and decision-making processes could be improved using RL.

On the one hand, with regard to the strategic and operational decision-making processes, studies on planning and scheduling processes seem to be a potential opportunity for aquaculture researchers and decision-makers.

On the other hand, RL algorithms can optimize aquaculture production processes, such as feed management, water quality control, harvest planning, disease management and energy optimization.

IV. Conclusions

The present study analyzes the existing literature on the application of reinforcement learning (RL) techniques in agriculture in order to point out future lines of development for aquaculture, especially for its decision-making processes. This has allowed us to reach a series of conclusions not only with respect to research, but also to the practice of the aquaculture industry.

On the one hand, a research gap has been detected in the area of operational research in aquaculture, since there are practically no published studies addressing the use of OR. Moreover, as can be seen in our results, the application of LR could be a good alternative in other areas, such as biology, environment, etc.

With respect to the aquaculture industry, the utilization of RL techniques in the field of aquaculture may enable operators to enhance operational efficiency, achieve cost reduction, optimize resource allocation, and effectively adapt to dynamic conditions. As a result, these advancements contribute to the establishment of more sustainable and profitable operations within the aquaculture industry. By leveraging RL-based solutions, a transformative revolution in aquaculture practices becomes plausible, driving substantial improvements in both efficiency and resilience.

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