From Industry 4.0 to Smolt 4.0 - Current Status, Industry Challenges and Directions for Optimized and Sustainable Production

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Abstract: The recent growth and development in salmon farming in Norway has led to a need for more robust and larger smolt/post-smolts. New and larger smolt production plants have been constructed to serve this need. However, these plants are still mainly run through manual labor, meaning that operations and management efficiency strongly depends on the experience of the farmers. This may effectually restrict the desired production growth. To enable the future sustainable growth of the industry, it is necessary to move from the experience-based production regime to knowledge-based and more objective methods. One way of achieving this is to implement solutions based on Industry 4.0 concepts. This paper outlines how Industry 4.0 can be adapted to smolt production through the Smolt 4.0 concept by targeting and analyzing the state-of-the-art within production methods in the smolt industry and evaluating how operations can be improved using Industry 4.0 principles. Three case studies demonstrating how this can be achieved are presented. The study concludes by discussing how more automation and autonomy in smolt facilities can counter challenges related to fish welfare, personnel risks, productivity, and profit.

Keywords: Agricultural robotics, Smart sensors, Precision farming, Digital Twins, Internet of Things, Automation

1. INTRODUCTION

The aquaculture industry is an important actor in global food production Food and Agriculture Organization of the United Nations (2016). With a growing global population and an increasing demand for farmed fish Naylor et al. (2021), the industry needs to increase production Food and Agriculture Organization of the United Nations (2016). While this general trend will contribute to reaching the UN goal of ending world hunger United Nations (2022), it also stimulates the development of new technological methods for intensive production forms that target high value products. The most prominent example of the latter is the salmon (Atlantic salmon, *Salmo Salar*) farming industry that has grown from humble beginnings around 50 years ago into a highly successful and profitable global industry. In 2020, the Norwegian salmon industry alone produced about 1.1 million tons of salmon of a gross value of around EUR6.1 billion The Norwegian Directorate of Fisheries (2022c). While much of this production increase has been realized in the sea-based ongrowing phase of salmon farming, there are also trends in land-based aquaculture towards developing and utilizing larger facilities and tanks Summerfelt et al. (2016). This has largely been stimulated by an increased need for smolt due to the growth in sea-based production and a desire to make the fish more robust before transfer to sea. In addition, the Norwegian farming industry is facing challenges with the production looses. The official statistics for production losses in salmon farming show that 113 million smolts The Norwegian Directorate of Fisheries (2022b) and 59 million adult salmon The Norwegian Directorate of Fisheries (2022a) were reported as lost in 2020, with similar numbers for the preceding years.

Since most of the volumetric production and hence most of the value gain occurs during the sea-based phase, the motivation to adapt new solutions for improved efficiency has been high for cage-based aquaculture Føre et al. (2018). This has stimulated a rapid rate of technological innovation and adaptation of new technology to reach production demands and address specific industrial challenges (e.g., lice treatment, escapes, feeding). The industry has invested large resources to solve these challenges, resulting in a shift in how industry actors use modern technology and technological competence. Some of the technological innovations already adapted in Norway include automated feeders AKVAgroup (2022); Abdallah and Elmessery (2014); Adegboye et al. (2020), advanced camera systems Kelasidi et al. (2020b), decision support tools Zhai et al. (2020) to assess fish welfare Noble et al. (2018), behavior and appetite Mohn Technology (2022), and biomass estimation tools AKVAgroup (2022); Li et al. (2020a). The industry is also making increased use of robotic solutions in applications such as net cleaning (e.g., by companies such as Sperre AS, Remora Robotics AS, Watbots AS) Bloecher (2022); Ohrem et al. (2020) and the use of remotely operated vehicles for inspection and light intervention operations AkvaGroup (2022); Bjelland et al. (2015); Amundsen et al. (2022). In addition, there are research efforts aimed at developing completely new fish production concepts including closed and semi-closed cages Chu et al. (2020), submersible sea cages Sievers et al. (2022), and ocean based farming concepts Chu et al. (2020). Since most of these concepts include increased use of tools such as advanced machines and systems, automation, and digital solutions, it is thus clear that sea-based aquaculture is evolving towards Industry 4.0.

The land-based production segment of aquaculture in Norway mostly consists of smolt/post-smolt producers, with a few exceptions where fully grown salmon are produced. Smolt production facilities are still largely based on the same management principles and methods as the first generation plants established in the 1980's but in larger scales. Several day-to-day labor intensive operations are manually executed, although with some exceptions such as automated systems for vaccination Ma et al. (2019) and feeding Skøien et al. (2018). Moreover, most monitoring tasks and decision making are based on manual observations and subjective analyses, rendering the assessments of, e.g., fish condition and welfare more dependent on the experience of the farmer.

The land-based phase of fish production in general and smolt production in particular is thus considerably less advanced than sea-based fish farming in terms of technology use and automation or autonomy. To harvest similar benefits from technology as those enjoyed by sea-based farming, smolt production needs to adapt a holistic approach to incorporating technology in operations. This can contribute to both more ethically sustainable fish production, increased productivity and profit, and a better working environment for employees. An additional effect to such high level improvements is that the resulting increased control can enable the production of more robust fish better suited for transfer to sea Øvrebø (2020); Ytrestøyl et al. (2015), and better health, safety, and environment (HSE) conditions leading to easier worker recruitment Engle (2021).

Introducing autonomous production facilities would result in a transformation similar to that experienced when Industry 4.0 was introduced in other industrial segments (e.g., oil and gas Elijah et al. (2021), automotive Ebrahimi et al. (2019), agriculture Liu et al. (2021)). The scope of this paper is to give a general overview of how land-based salmon production units can be further developed by adapting elements from the Industry 4.0 paradigm in the *Smolt 4.0 concept*. The paper focuses on the current situation in Norway, but is expected to be highly relevant to land-based fish farming companies and institutions internationally in general.

Section 2 describes the principles of Industry 4.0, and its potential application to livestock production, and the practices in smolt production in more detail, thereby outlining the knowledge background. Following this, Section 3 breaks down common operations in smolt production into specific challenges that can potentially be managed through technology. Section 4 then outlines three concrete case studies describing how fulfilling the research needs can lead to potential industrial applications and innovations. Finally, Section 6 summarizes the study and discusses the findings.

2. BACKGROUND

2.1 Industry 4.0 and smolt production

The Industry 4.0 paradigm Industry 4.0 (I4.0) refers to the fourth industrial revolution where the focus revolves around cyber-physical systems (CPS) and their introduction into the workplace Vaidya et al. (2018). The introduction of such systems entails an increased focus on different aspects such as digitalization, big data, Internet of Things (IoT), digital twins, blockchain technology, artificial intelligence, objectivity, robotics and increased levels of automation into all aspects of production, business and customer experience and acquisitions Ibarra et al. (2018); Sharma et al. (2022). Many industries such as the oil and gas Elijah et al. (2021), automotive Ebrahimi et al. (2019) and agriculture sectors Liu et al. (2021) are motivated by the benefits of I4.0 and are consequentially striving to adapt an I4.0 model.

This has resulted in the application of fully unmanned, remote controlled oil and gas platforms osH (2019), and that the automotive industry is now exclusively using highly automated production lines and has started to adapt big data analysis to, e.g., identify customer needs Deloitte (2015). The agriculture industry has also started integrating components of I4.0, such as automated systems for sowing Brown (2018), inspection and harvesting of crops Tian et al. (2019), planning crop layout FAO (2017), and making predictions regarding yields based on previous historical data Leavitt (2022).

Industry 4.0 and aquaculture Some aspects of I4.0 are already partly being implemented for some operations in sea-based aquaculture. Prominent examples include feeding cameras that help track fish appetite during feeding Li et al. (2020b), automatic net cleaner robots Ohrem et al. (2020, 2021), and methods for autonomous inspection of nets in sea cages Kelasidi et al. (2020a); Schellewald et al. (2021); Amundsen et al. (2022); Su et al. (2021).

Although this adaptation has not come as far for smolt production as it has for sea-based fish farming, recent trends where the size of the production units has increased Summerfelt et al. (2016), as well as the number and size of fish in each tank, underline that this is a necessary next step for the industry. So far, the development of technologies in smolt production has been aimed at specific challenges, such as automation of sorting, counting and vaccination of fish, some degree of light and water temperature control Noble et al. (2018), and using Recirculating Aquaculture System (RAS) to recycle and reuse the water Bregnballe (2015). To fully exploit the benefits of an I4.0 approach, the industry will need to transcend from this case-by-case practice to an approach where technology and automation are assimilated into every step of the produc-

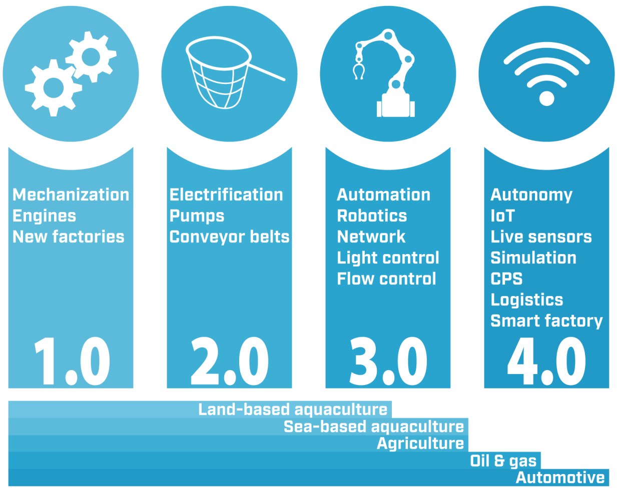


Fig. 1. Industry 4.0 and smolt production units (Illustration by Mats Aarsland Mulelid).

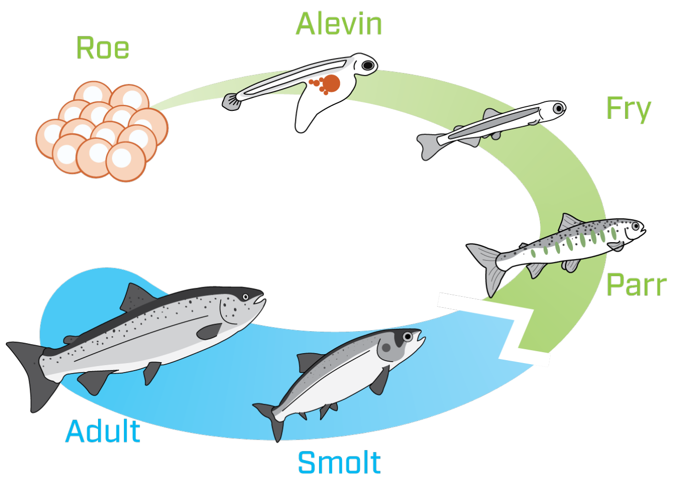


Fig. 2. The life stages of Atlantic Salmon (Illustration by Mats Aarsland Mulelid).

tion chain (Fig. 1), as has been the recipe for previous successful transitions to I4.0 in other segments.

2.2 Status and Operations in smolt facilities

The salmon life cycle Salmon go through a set of life stages, as illustrated in Fig. 2 Jobling et al. (2010). The first four stages (egg, alevin, fry, parr) are conducted in fresh-water and ends with the smoltification process during which the fish metamorphose into tolerating saline water, followed by the two sea-water stages (smolt, adult). This is also reflected in the practices of modern aquaculture, as the production chain is similarly split between corresponding freshwater and seawater phases that are tailored to serve the needs of the fish.

Although the roe phase is sometimes conducted in specialized hatcheries, the land-based phase is often conducted in its entirety in smolt facilities. To successfully introduce I4.0 principles to smolt production, it is important to understand the different stages in this phase and how these can be improved through I4.0. In the following, the different stages of the land-based phase including smoltification will be briefly described, highlighting the most common operations for each stage.

Life stages and common operations in aquaculture **Roe:** The salmon life cycle starts with fertilized eggs (roe) that are first placed in small and shallow hatching tanks and spread out onto a substrate. The substrate separates and fixes the eggs in place, and ensures a continuous water flow that mimics the situation in a river. Incubation time before hatching depends on water temperature and typically lasts around 60 days for salmon. Once the fish hatch, the substrate provides the emerging alevin with shelter. **Operations:** Roe inspection and removal of damaged or dead roe, monitoring, and control of water parameters.

Alevin: Newly hatched alevin have yolk-sacks containing enough nourishment for the first 4-6 weeks of their lives. At this stage, the fish seek shelter in the substrate in the hatching tanks, mimicking the behavior in the wild where alevin seek shelter among rocks in sections of the river with low current speeds. **Operations:** Removing remains of hatched roe, inspecting the fish, removal of deformed and abnormal fish, monitoring and control of water parameters.

Fry: When the alevin has consumed their yolk-sacks they enter the fry stage, where they start swimming towards the surface and filling the swim bladder for the first time. This increases their stability and swimming abilities. At this point the fish starts to swim freely in the water masses consuming food, and are therefore moved to small start feeding tanks where they are given their first formulated feed. Feed regulation and pellet size determination is of great importance at this stage. **Operations:** Rapid movement from the hatchery to feed tanks, sorting fry from alevin, monitoring of fish behavior and growth, control of water parameters, control of feed size and distribution.

Parr: When the fry have successfully started actively feeding and gained weight, they transform into the parr stage where they develop stripes on the sides and camouflage colors. In nature, these will often be dark stripes and a dark green and brown color, but in aquaculture they may assume different colors (e.g., white if the tanks are white). The parr stage is the longest stage in the freshwater phase and may last for several years in nature, but is usually shorter in aquaculture (i.e., less than a year). **Operations:** Monitoring of behavior and fish condition, splitting and sorting, vaccination, removal of deformed and dead fish, monitoring and control of environment and water parameters, feeding.

Smolt: Parr transform into smolt through a metamorphosis called smoltification Solomon et al. (2013); Svendsen et al. (2021). The fish undergo a series of physical, morphological, and behavioral changes. The osmosis regulation through the gills are changed Solomon et al. (2013), adapting them to an environment with higher salt concentration Noble et al. (2018) and altering their condition factor and colors. Smoltification is necessary for the fish to survive in salt water, but can be reversed if the fish are kept in freshwater Fjelldal et al. (2018). **Operations:** Identify when the fish have fully smoltified, monitoring and control of environment and water parameters, sorting and splitting parr and smolt, feeding.

Summary of daily Operations in smolt Facilities Table 1 summarizes the most common operations in smolt production identified above, and considerations on their current level of automation Parasuraman et al. (2000). Note that some of the stage-specific operations are covered by more generic terms in the table (e.g., "population monitoring" includes inspection and monitoring of eggs, fry, parr and smolt, while "dead fish and waste removal" includes also the removal of dead eggs/egg remains).

3. RESEARCH AND INNOVATION CHALLENGES IN SMOLT OPERATIONS

Table 1 represents the day-to-day operations and are periodic, repetitive and typically well-defined. Thus, these operations are strong candidates for targeted increased objectivity and level of autonomy, and serve as a starting point for identifying the research and innovation challenges that need to be solved to improve objectivity and automation in smolt production. In the following, the current status and main challenges with the operations in Table 1 are presented, serving as a basis for establishing research needs and defining challenges towards improved objectivity and automation.

3.1 Water quality monitoring

Status Some of the most common water quality parameters are temperature, dissolved oxygen (DO), CO_2, Ammonia, Nitrate, NO_2-N, Nitrogen, H_2S, total suspended solids, chlorine, and pH Lucas et al. (2019). Temperature and DO are identified by fish farmers as the most important water quality parameters Noble et al. (2018) and are often measured using sensors placed in the tank on a continuous basis. It is also recommended that salinity (in addition to water flow velocity) Ytrestøyl et al. (2020), pH, and CO_2 Fivelstad et al. (2003) are measured periodically Noble et al. (2018). Most other parameters are estimated by taking water samples and analyzing these using laboratory equipment. Although there are examples of facilities that measure only in reference tanks, water quality is often measured in each tank in modern RAS facilities.

Challenges Sensors used in land-based fish farms are typically deployed underwater for extended periods and may suffer from fouling and long term drift, leading to low reliability and hence maintenance and calibration Noble et al. (2018). Moreover, laboratory measurements can only give answers after the analysis is performed and cannot provide information *in-situ*.

3.2 Sensor and equipment maintenance

Status Sensor and equipment maintenance mainly involves cleaning, removing biofouling, equipment disinfection, changing wear parts, and periodic sensor calibration. This is done to secure correct measurements and fully operable equipment and sensors, leads to proper control over the tank conditions, and helps avoid lowered accuracy, stationary offsets and/or drift over time. Almost all such operations are executed manually today.

Challenges Proper calibration of a sensor may be challenging in smolt tanks as the sensors are often submerged, and since the work requires knowledge about the given sensor system and advised calibration procedures. Furthermore, calibration and maintenance of sensors and other equipment is time-consuming, and may lead to production downtime. Properly cleaned, disinfected, and calibrated sensors and equipment are critical for ensuring accurate measurements of the conditions of and operations involving the fish.

3.3 Light and temperature control

Status In several modern smolt facilities, light and temperature are controlled by automated systems. Artificial light is used to simulate circadian and seasonal variations, and thus affect social interactions, resting behavior, exploration and feeding. Light control can also be used to stimulate smoltification, improving control over the production Noble et al. (2018). Thermal control is important because temperature largely controls the metabolic rates in fish, and can hence be important when seeking to steer fish growth and feed intake.

Challenges Since available commercial solutions can be adapted to have full control of light and temperature in land-based production units, future research efforts could be targeted to identify how temperature and light can be used as inputs for decision support systems related to fish behavior and health.

3.4 Fish population monitoring

Status Daily inspection of the fish in smolt facilities is most often done by employees reviewing sensor data and inspecting the fish visually either through cameras or by direct observation Noble et al. (2018). This typically entails observing fish behavior and other visually detectable indicators of reduced welfare such as wounds, deformities, potential disease indicators and dead fish, and may also include fish health service personnel Noble et al. (2018). Some companies deliver camera systems with or without integrated computer vision techniques for real-time monitoring and inspection of fish status (e.g., Scale Aquaculture AS).

Challenges Subjective evaluations and decision making on fish conditions and states rely heavily on employee experience and competence. Moreover, purely manual inspections may not provide a complete picture of all individuals within the population, which may ultimately result in sub-optimal decisions and even mistakes. This is further complicated by that the increase in tank sizes seen in the industry renders obtaining a full population overview through manual means even more difficult.

3.5 Dead fish and waste removal

Status Some fish die during smolt production due to various reasons such as deformities, disease, inter-individual aggression / hierarchy formation limiting access to food causing starvation or malnutrition, or potential rough handling during an operation. Moreover, waste materials such

Table 1. Daily operations

Task	**Level of automation**
Initial inspection	Manual
Water flow control	Control system
Water quality monitoring	Sensors manually inserted into tank
Sensor maintenance	Manual cleaning and calibration
Equipment maintenance	Manual
Light and temperature control	Control system
Population monitoring	Manual
Dead fish and waste removal	Manual with some level of automation
Splitting and sorting biomass	Personnel-operated machines
Feeding	Automated feeders, manual refill
Feed size regulation	Manual, tables and experience
Biomass estimation	Manual techniques or weight-cells
Tank cleaning	Manual
Vaccination	Automated machines
Smoltification tracking	Manual testing

as uneaten feed particles and feces will accumulate in the tanks during production. Both these elements need to be removed from the tank to avoid detrimental water quality. Dead fish are typically removed manually or using an installed dead fish collection system that removes the fish from the bottom of the tank Timmons et al. (1998) or from the surface, after which they are removed manually from the system. Waste materials are often removed using filters on in- and out-flux water Timmons et al. (1998), surface treatments applied to the tank wall, or by controlling the current to passively transport particles to waste collection areas Gorle, J. and Summerfelt, S. T. and Terjesen, B. F. and Mota, V. C. and Marchenko, Y. and Reiten, B. K. M (2016); Timmons et al. (1998); Gorle et al. (2020).

Challenges The removal of both dead fish and waste materials from the system is still mainly done manually. Existing systems for automated waste collection are difficult to install after a facility has been built and most often leave the dead fish or waste material within the tank until they sink to the collection point. In addition, the management of the collected waste and dead fish also introduces challenges related to deposition or recycling/reuse of these in further value chains.

3.6 Tank cleaning

Status Algae and other fouling species will over time colonize the tank walls and together with suspended waste materials that settle on the wall accumulate into an unwanted film on all tank surfaces. Since this will reduce water quality and increase risk for diseases, it is thus necessary to conduct periodic cleaning of the tanks, a process that is usually done manually using high pressure hoses and other cleaning equipment between production cycles. This may increase the downtime of the tanks, leading to reduced productivity. Cleaning tanks while in use would thus be an attractive prospect as this could both improve productivity and increase cleaning frequency such that the risk of waste build-up along the tank walls that may negatively impact the water quality is reduced. In addition to the tank itself, pipes and other overall equipment in the facility need to be cleaned to avoid the buildup of toxic levels of H_2S gas.

Challenges High-quality cleaning with minimal physical stress on human personnel and minimal downtime of the tanks is challenging to achieve. Existing solutions for cleaning, such as lowering the water level and cleaning exposed parts of the tank, are generally not desirable as waste particles from the tank walls may then detach and enter the tank before being removed by the flow. The same applies to solutions where the population is moved to a temporary holding tank while cleaning takes place, as this is labor intensive and can be stressful for the fish.

3.7 Biomass estimation

Status Efforts have been made on biomass estimation of individual counting in land-based facilities using, e.g., computer vision de Ávila et al. (2021), but precise biomass estimation remains one of the main challenges of the industry. Biomass estimation in land-based facilities is today performed either by sampling the population (e.g., direct measurement) Li et al. (2020a), using predictive models, or a combination of these. Biomass estimates can also be corrected when more precise calculations are available, e.g., after vaccination and fish counting during operations Aunsmo et al. (2013). The most common method for biomass estimation involves crowding the fish, catching a representative number of individuals, weighing them, and then extrapolating the weight of the entire population from these measurements. However, the industry is also starting to use camera-based biomass estimation systems that use computer vision to estimate the weight of free swimming individuals Li et al. (2020a), some of which are already in the market for sea-based aquaculture, including those produced by Optoscale (BioScope), CreateView (CView 360) and Scale Aquaculture.

Challenges Handling fish for manual sampling demands a high degree of manual labor, will stress the fish, and does not guarantee a good result unless the individual variability is very low. It is also challenging to gauge the biomass based on the mean weight without knowing the number of individuals in total within the population.

3.8 Splitting and sorting biomass

Status Size grading and sorting machines (e.g., Vaki Ltd.) that grade and sort fish by size to keep the size of the tank population as uniform as possible are commonly used Gabriel et al. (2016). This entails using specialized equipment where the fish are transported onto a horizontal surface grid and then fall into differently sized holes depending on their size, thereby enabling splitting and sorting the biomass based on individual size. Sorting may also be done automatically during vaccination using machines.

Challenges While some aspects of splitting and sorting is automated, manual labor is still needed to set up the equipment, determine when to start (often part of the production plan), and start the process. Sorting also involves handling the fish and may impact welfare.

3.9 Biomass transport

Status Unlike many other operations, transportation of fish between tanks has been automated by utilizing fish pumps (e.g., Skala Maskon AS). Such pumps are also often used in operations such as vaccination or grading that reduce the need for manually moving the fish to and from tanks during different operations.

Challenges Pump-based transportation can be very stressful for the fish and may lead to physical trauma due to sharp bends or sharp edges inside the pipes or rapid pressure changes.

3.10 Vaccination

Status Vaccination is today mostly done using vaccination machines (e.g., Skala Maskon AS) that can both dose and deliver vaccines autonomously. These units use computer vision to detect the fish and decide where to place the syringe Schat (2014), and provide highly accurate biomass results and population numbers because all fish are handled individually.

Challenges While most of the vaccination process is automated, the fish still need some handling to be transported into the vaccination machine.

3.11 Feeding

Status Feeding is arguably the most important operation in the land-based phase. The amount of feed needed for each individual fish depends on factors such as fish size, feed composition, and water quality parameters Sun et al. (2016), and the suitable pellet size will increase as the fish grow larger Bureau et al. (2003). While feed is usually distributed to the population by automated dispensers Bureau et al. (2003), the amount of feed delivered to each tank is usually a subjective decision based on observations and farmer experience, and the dispensers also often need to be filled manually. There are products for cage-based (e.g., UMITRON, Aquabyte AS, and CageEye) farming exploiting machine learning to estimate the required feed amount in a more objective and automatic fashion Chen et al. (2020), but these are not yet adapted to tanks. Furthermore, fully automated feeding systems (e.g., Vard Aqua AS, VAKI, and Laksesystemer AS) that can hold feed of various sizes and supply multiple tanks exist, but have yet to see widespread adaptation by the industry.

Challenges Feed delivery is largely automated. Tasks such as dispenser refilling and hand-feeding during initial stages are still manual, being both time-consuming and labor intensive Bureau et al. (2003). In addition, choosing the right composition, size, and the amount of feed is often based on production plans and experience-based insight.

3.12 Smoltification tracking

Status The industry employs two main strategies for determining smoltification degrees in farmed fish. The first method involves sampling gill tissue for subsequent laboratory analysis to quantify fresh- and sea water ATPase. In the second approach, a number of individuals are exposed to saline water for 48-72 hours, after which blood is sampled from the fish and the sodium chloride content is analyzed. Since both these approaches are very invasive, less invasive principles have been explored in research. For instance, hyperspectral imaging coupled with machine learning has been proven able to estimate smoltification in salmon with 85-100% accuracy Svendsen et al. (2021).

Challenges The main strategies used in this area are suboptimal, as they are terminal and have negative impacts on fish welfare in inducing handling stress, and exposing potentially unsmoltified individuals to sea-water. They also feature long waits between testing and results, and operate on small sample sizes that may not be representative for the whole tank population Svendsen et al. (2021). While new methods such as hyperspectral imaging systems with machine learning are attractive they are not ready for industrial application. Desmoltification is a general challenge that can cause major mortality events and other challenges, and hence implies an even stronger motivation for accurately assessing when the metamorphosis has taken place Svendsen et al. (2021).

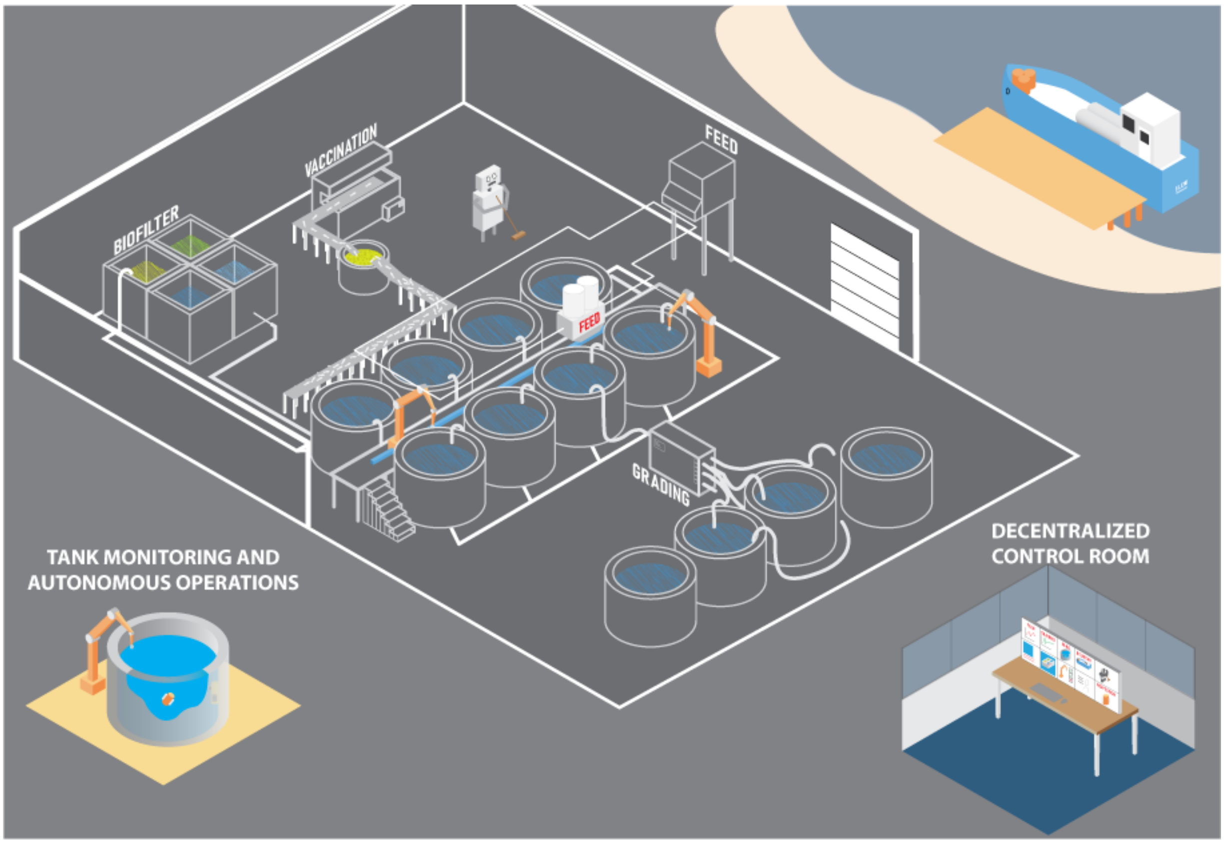
4. CASE STUDIES AND CONCRETE SOLUTIONS

This section presents and discusses three case studies, which suggest directions for research that can lead to industrial applications and innovations.

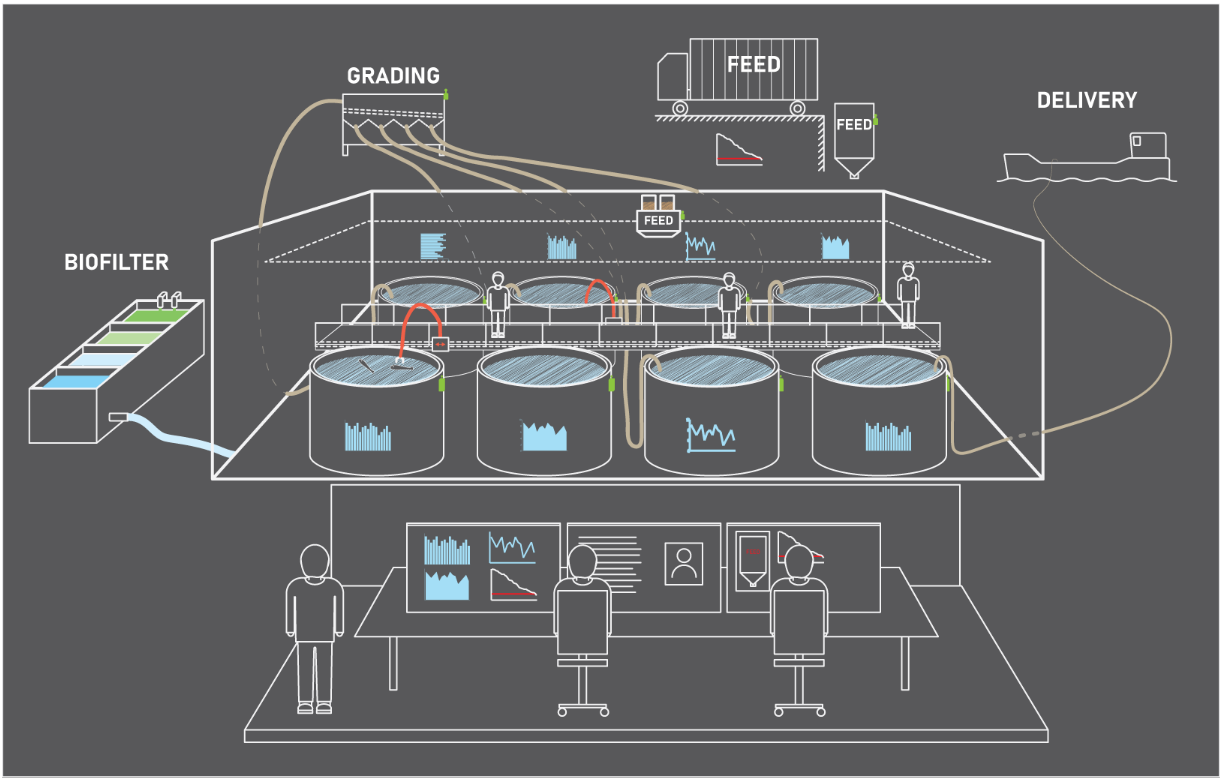
Fig. 3 illustrates what a smolt production facility in the I4.0 paradigm might look like. While no such holistic concepts have been fully realized yet, solutions to several of the previously described challenges can be partially or fully implemented by adopting existing technology and solutions.

The initial study towards this direction has been performed as part of the research in the Autosmolt2025 project Eilertsen et al. (2021). In particular a questionnaire was handed out to the project partners involved in land-based aquaculture to share their practices and thoughts around the topic of automation principles and optimized smolt production.

This questionnaire contained a range of questions covering several topics such as which tasks they considered most important, how they use technology and automation today, and how they foresee these tools could serve to improve future operations in such facilities. The outcomes of the questionnaire implied that water quality monitoring, fish population monitoring, dead fish and waste removal, tank



(a) Automation and robotics



(b) Smart-factory

Fig. 3. Illustration of a future land-based smolt production facility integrating several components of I4.0, such as autonomous operations, robotic system, digital twins, artificial intelligence, decentralized control room, and high quality data acquisition from sensors (Illustration by Mats Aarsland Mulelid).

cleaning and biomass estimation were among the areas in which the industry would most like to have a stronger degree of automation. To better illustrate how these aims can be addressed by research and innovation processes, three case studies were outlined:

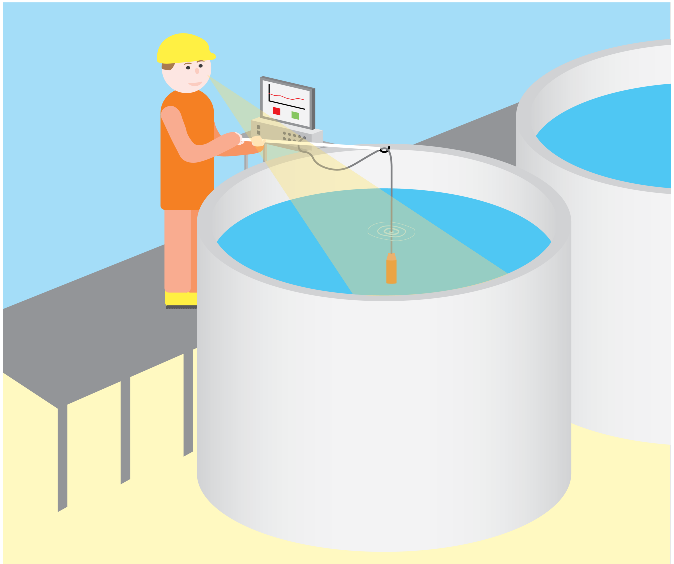
(1) **Self-monitoring rearing tanks**
Aim: Autonomous data collection and analysis from diverse sensors
(2) **Autonomous tank operations**
Aim: Autonomous physical operations
(3) **Smolt 4.0: Optimized smolt production**
Aim: Holistic system for high level operational planning and decision making for autonomous tank operations based on data from self-monitoring tanks

The case studies can be considered consecutive in the sense that one needs case studies 1 (data collection) and 2 (automated physical operations) to realize case study 3 (high level process control), and may also serve as a roadmap and starting point for how future research and innovation processes can better target Smolt 4.0.

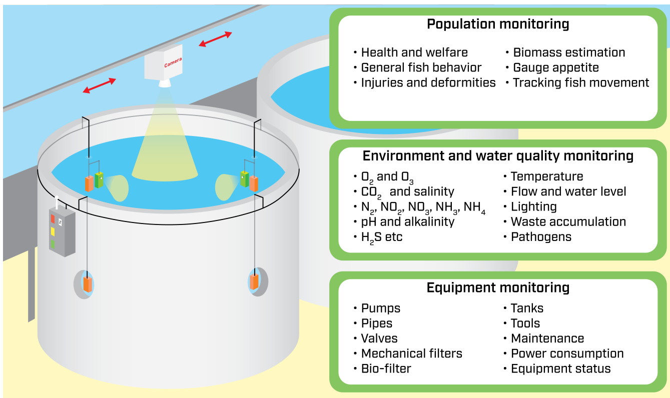
4.1 Self-monitoring rearing tanks

The core technologies needed to develop self-monitoring tanks have existed for some time and have successfully been applied in other industries. Base components would be intelligent sensors able to quantify important variables in the tanks, networks (cabled or wireless) for transferring data from the tank, and a centralized hub responsible for collecting, processing, and storing the collected data. Furthermore, methods from sensor fusion could be used to combine data from different systems to generate new data types that could provide better insight into system dynamics than each of the systems by themselves, and that could complement other data sources. The collected outputs from such systems could either be presented directly to the user for their perusal in decision making, or combined with an alarm system to elicit alarms when surpassing critical limits in key variables. There are examples of companies offering solutions (e.g., Blue Unit AS) that measure 12 different water quality parameters throughout a given facility and offer benchmarking software for the results.

The transition from the current manual and experience-based practices to a fully autonomous and optimized holistic solution for self-monitoring tanks is illustrated in Fig. 4. Three concrete application areas have been identified to be particularly important for self-monitoring tanks: 1) population monitoring; 2) environment and water quality monitoring; and 3) equipment monitoring. Consequently, Internet of Things (IoT) and digitalization are expected to be central. In addition to blockchain technology for traceability, devices and system communicating and transmitting information in an IoT framework will be crucial in the these areas for securing flow of information, monitoring, decision making or decision support tools and both manual and automatically performed actions related to the farming processes. In the following, the aforementioned application areas will be used to outline the key requirements of a monitoring system, the use of data and the required technology in greater detail.



(a) Manual monitoring



(b) Autonomous monitoring

Fig. 4. Illustration of self-monitoring rearing tanks concept (Illustration by Mats Aarsland Mulelid).

Population monitoring The most important components needed for autonomous population monitoring are sensors or instrumentation for observing the fish. While novel camera solutions and computer vision techniques are seeing increased use in both the aquaculture industry and research Zion (2012); Saberioon et al. (2017), other solutions such as hydroacoustic instruments (e.g., echo sounders, sonars) and biosensors/telemetry can also shed light on the population in tanks Føre et al. (2018). Such solutions can be used to observe both group-based and individual-based operational welfare indicators (OWIs), representing a practical approach to score the welfare of the fish at the farm Noble et al. (2018), that can be combined into common data types to provide insight into the dynamics within the population. Moreover, combining the data from such solutions with predictive fish models (e.g., Føre et al. (2009); Stavrakidis-Zachou et al. (2019)) could be a foundation for alarm or decision support systems able to predict events in the future.

Autonomous population monitoring will be a tool for improving farm management by enabling the farmer to adjust feeding, lighting, and other management features continuously according to the fish responses. Moreover, if certain operations (e.g., when a certain population was split, sorted or merged) are logged and registered during production, population monitoring outputs can be used to analyze how the fish respond to these. Continuous monitoring would also enable logging the history of a population and identify how population properties changed during production, improving product traceability from egg to customer. The most relevant parameters related to population monitoring are shown in Fig. 4

Environment and water quality monitoring The principal components in a system for water monitoring are sensors able to measure the values most critical during production. A perfect system for objective and optimized monitoring of the environment would include sensors capable of measuring every relevant parameter continuously and reliably, at any point of interest within tanks (see Fig. 4).

Although some important factors such as Nitrite, Total Ammonia Nitrogen (TAN) and H_2S are possible to measure using lab equipment, to the authors' knowledge, there exist no commercially available sensor solutions capable of measuring these on a continuous basis. However, systems that perform continuous water quality analysis of some parameters, that traditionally are done using lab equipment, do exists and may serve as a platform for realizing such solutions that measure most or all parameters continuously (e.g., Blue Unit (2022)). Moreover, there are promising ongoing research efforts within wireless water quality monitoring platforms that can predict changes in water quality quite accurately Zhu et al. (2010); Peng et al. (2020). Methods for automatic calibration of the included sensors would be a reasonable feature for self-monitoring solutions. There exist such methods, e.g., for temperature Orzylowski et al. (2000) and camera or range estimator sensors Geiger et al. (2012) that could be adapted and potentially extended to other types of sensors.

If a holistic solution for environmental monitoring turns out to be too expensive for deployment in all tanks, an alternative approach could be to design a modular sensor system possible to move between tanks, either autonomously or by some auxiliary system. There are examples of robotic sensor carriers for water quality measurement capable of autonomous navigation and measurement of water quality parameters being researched for aquaculture application Huang et al. (2020).

Similar to population monitoring, continuous water quality measurements could be useful for adjustments and feedback control of, e.g., pumps and filters to dynamically improve culture conditions. Such data could also be compared with historical data and production logs, thereby enabling predictions of trends and providing guidelines/decision support on what to do in a given situation. Together, these impacts could increase the ability to steer water quality to desired states and thereby enable more predictable production conditions which is beneficial to achieve similar fish qualities across production batches.

Equipment monitoring Just like for population and water quality monitoring, sensors would be the core components of equipment monitoring systems. The most common equipment related to monitoring components are listed in Fig. 4. However, unlike for the others, several of the sensors required for this already exist and are being used by the industry. Some of the more complex system components such as pumps, valves, mechanical filters and bio-filters are often equipped with sensors for gauging pressure, flow, power consumption and other parameters describing their condition and state. More inert components such as tanks, pipes and other structures can be monitored using standardized sensors for e.g., strain, pressure and flow that are designed for industrial applications.

By monitoring equipment, it is possible to optimize production also in this aspect. For instance, optimizing power consumption would reduce the cost of production, while the implementation of predictive maintenance systems Selcuk (2017) would reduce downtime, and in turn increase fish welfare and production. This would also enable the streamlining of the process of ordering new parts or parts that are soon to be worn out preemptively. New innovations in technology will also allow for monitoring the bio-filter in RAS facilities to a larger extent, and also monitor for pathogens within the environment.

4.2 Autonomous tank operations

While there is a foundation for automatic or autonomous tank cleaning systems in existing tank cleaning applications, other operations are not equally blessed with similar examples from other sectors. However, most such operations would require several key components that are possible to find commercially today, foremost being robotic vehicles able to navigate within a tank, and robot manipulators for underwater use. Such solutions should also have a way of perceiving the situation through sensors and instruments. This would be crucial both to ensure that the operation is executed properly (e.g., by monitoring the results), and to ensure that the operation is as gentle and non-invasive as possible with respect to fish and structural integrity.

Based on their importance and labor intensiveness as perceived by the industry Eilertsen et al. (2021), three key application areas of autonomous tank operations are 1) feeding; 2) tank cleaning; and 3) dead fish removal. In the following, these application areas will be used to describe the core features, properties, and uses of autonomous tank operations.

Feeding An illustration of a manual (semi-automatic) and fully autonomous feeding operation is shown in Fig. 5. Fully autonomous feeding operations would require systems with abilities to transport and dispense feed to the fish, choose the proper feed dose, feed type and size, and accurately estimate fish appetite. This would be a complex system that requires a synthesis between technologies for actuation and intervention and monitoring/sensing systems. Some automatic feeding systems already exist and could serve as a foundation for an autonomous feeding system in combination with solutions for monitoring fish and feed. Examples of such systems include the Exact Feeding Robot that moves between all tanks in a facility or Exact Mini Feeder and Belt Feeder that are installed on each tank, produced by the company Vard Aqua AS. Other relevant solutions such as a small feeding vehicle that moves on the surface to distribute feed over a certain area within a specific time period Deroy et al. (2017) could also be relevant components in such systems.

Autonomous feeding operations could enable feedback control for feeding where feed delivery is steered by fish appetite and required feed size. Moreover, such systems could also enable autonomous filling of feed containers, which is a laborious task to do manually.

Tank cleaning An autonomous cleaning system should identify when cleaning is necessary, initiate the cleaning procedure, perform the cleaning, ensure that excess waste is collected and get the cleaning approved before the tank is used again. These systems would need to be created by combining different components handling the different necessary tasks. Adaptation and implementation of fully autonomous tank cleaning operations requires novel research methods and new innovative products, which may be based on inspiration from other industries such as sea-based aquaculture Ohrem et al. (2020), ship cleaning Le et al. (2021) and more. Cameras with integrated computer vision and machine learning methods could be used by such systems to estimate amounts of cleaning waste, when cleaning is necessary, and whether the cleaning system performed satisfactory or not. The cleaning activity could be executed by a continuously moving cleaning system, a robotic manipulator mounted on a rail system, or by a self-propelled robotic system equipped with a cleaning tool Haugaløkken et al. (2021) (e.g., soft brushes or water blasters Skeide (2020b); Nissen (2021)) such as the one presented in Fig. 6. While there has been on-going research on self-cleaning tanks for several years Timmons et al. (1998); Gorle et al. (2020), most recent research efforts seem to move towards robotic solutions for regular cleaning Koyama and Yonekura (2018); Skeide (2020a). There are also commercial solutions that may be useful components in such systems. Some examples are units mounted on the tank that clean tank walls and floors (e.g., Oceans Designs AS), autonomous underwater vehicles aiming to clean and inspect the tank and collect dead fish in large production units, and a moving cleaning vehicle developed by Mørenot AS.

Autonomous tank cleaning operations would enable a more continuous cleaning regime where the buildup of biofouling and other substances is kept low, as is the resulting waste material. This will improve water quality and thus provide a more healthy environment for the fish without being a labor intensive process. Regular cleaning can also prevent the establishment of bacteria or microbes on the tank walls, rendering a waste collector system excessive.

Dead fish removal Autonomous dead fish removal could be enabled through robotic solutions that are able to detect fish, verify if the fish is dead and remove fish. An illustration of how this operation can be done is given in Fig. 7. The main components of such solutions would be suitable robotic hardware, perception systems, and software that would allow the desired operation to be conducted in a safe and efficient manner.

Irrespective of whether the robotic platform is free-moving inside, fixed to or outside the tank, it would need a manipulator with an appropriate gripper tool Pedersen et al. (2020). To avoid damaging the fish while collecting them, specific tools and components such as soft grippers and complex planning and control systems would be needed. Advanced camera and computer vision systems would be necessary both to provide feedback control on the motion of the manipulator, to do other tasks such as localizing the fish, and running "dead-or-alive" classification of the fish before collection.

Autonomous systems that continuously search for and remove dead fish would likely contribute to a better production environment, as dead fish inside a tank will be a potential reservoir for pathogens and other unwanted substances. Moreover, since manual dead fish removal is a laborious and dirty job, automating this task could contribute to improved HSE conditions.

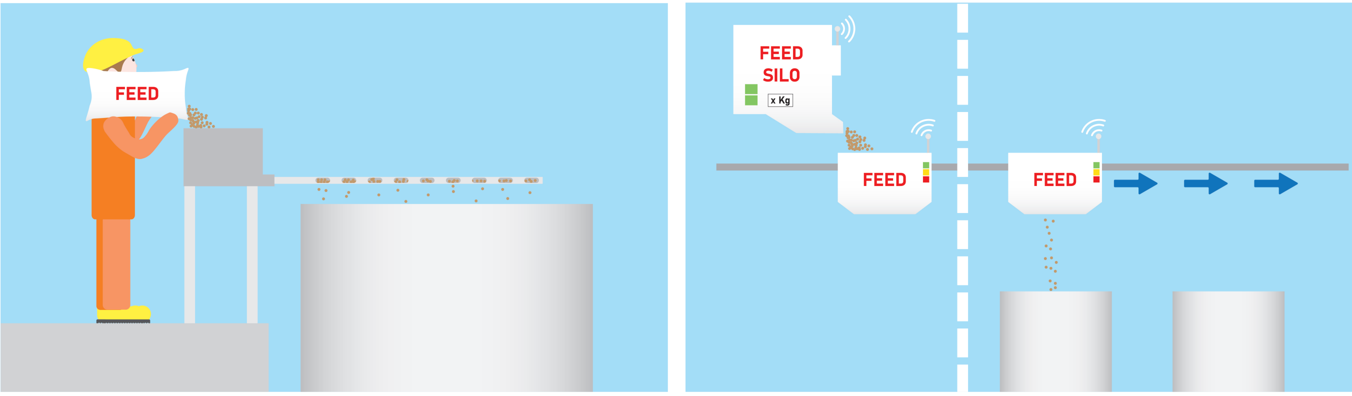
4.3 Smolt 4.0: Optimized smolt production

The final case study, Smolt 4.0: Optimized smolt production, is an umbrella term representing the synthesis between self-monitoring tanks, autonomous tank operations and high level decision support. The resulting combined system would be capable of gathering data through the sensors integrated in an IoT framework, analyses to provide reliable state estimates and predictions continuously, application of these for environment and population control purposes, and perform autonomous tank operations. This would enable optimization smolt production processes such that it is possible to produce robust, high quality smolt while securing both fish and employee welfare. Another aspect of such a solution would be traceability and repeatability in the sense that the farmer through feedback control can keep production conditions similar across production batches. Since the production environment is important for the development of the fish, it is possible to keep the smolt quality more similar between production cycles. An illustration of what such a system could look like can be seen in Fig. 3.

To become complete, Smolt 4.0 would also need to account for other more practical aspects such as fish logistics and how to streamline the acquisition of parts, feed and vaccines, as these are equally important factors in determining production efficiency and precision. In this area, there are examples of research into optimizing logistics in the manufacturing industry with regards to procurement and production Fang et al. (2015) that could be transferable to the aquaculture industry as well. Improved logistics can also reduce production costs by enabling the farmer to purchase, e.g., parts and feed at times when prices are low rather than when their need is immediate. Moreover, efficient logistics can reduce the time personnel have to use on such tasks, allowing them to focus their competence on more complex tasks related to production.

5. SMOLT 4.0 - SPECIFICATIONS AND DESIGN REQUIREMENTS

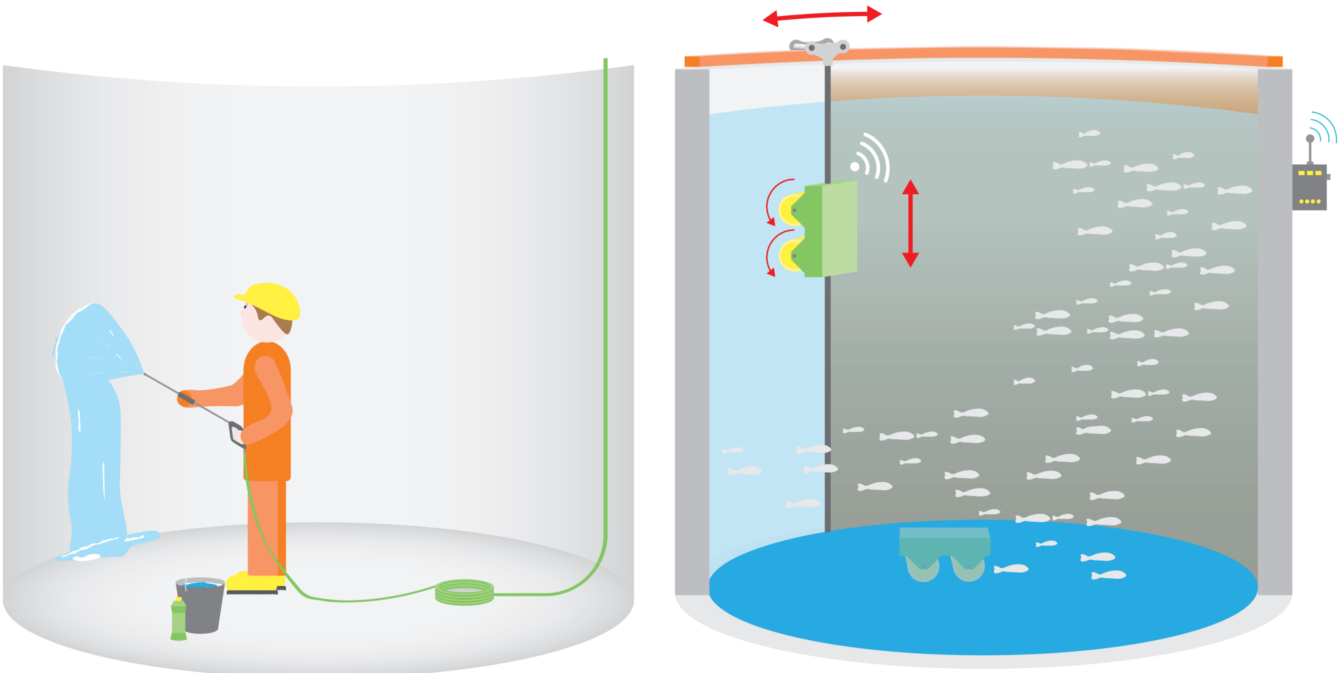
This section uses the Seatonomy method Grotli et al. (2016) to analyze the application of Smolt 4.0 in greater detail and specify the design requirements. The Seatonomy method is a structured framework used to analyze challenges related to automation in marine environments that



(a) Manual (semi-autonomous) feeding operation

(b) Autonomous feeding operation

Fig. 5. Illustration of feeding process in land-based production units (Illustration by Mats Aarsland Mulelid).



(a) Manual tank cleaning

(b) Autonomous tank cleaning

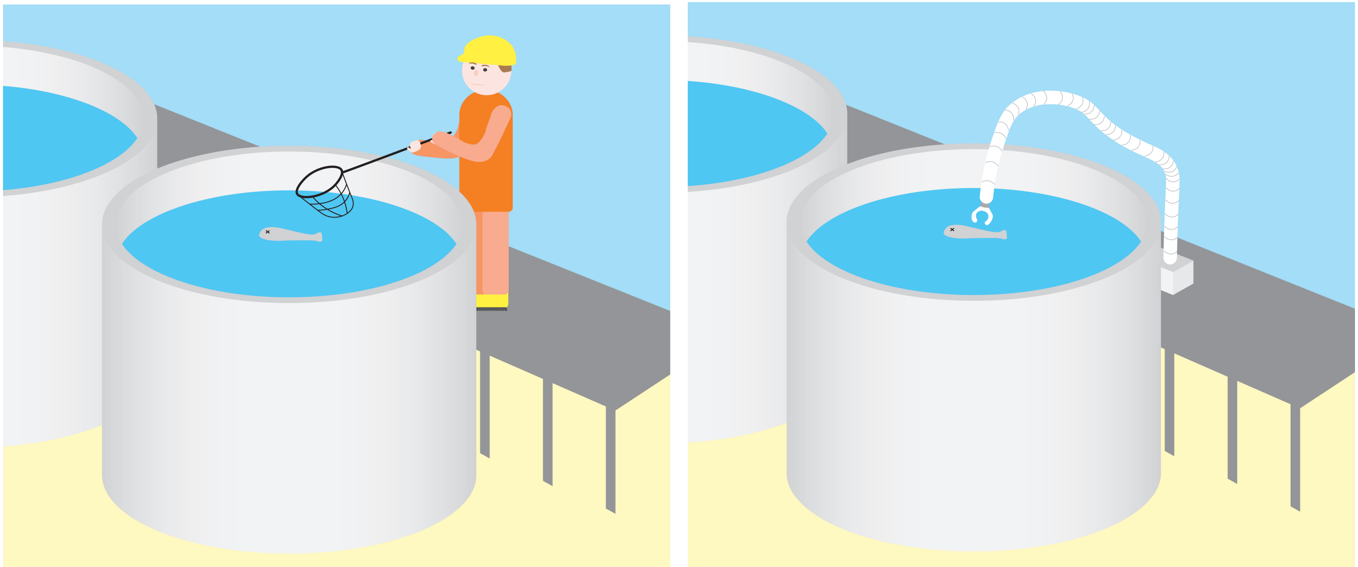
Fig. 6. Illustration of tank cleaning process in land-based production units (Illustration by Mats Aarsland Mulelid).

was originally designed for autonomy and robotics but that is also possible to generalize and apply to monitoring and logistics optimization. In the following, a summary of the Seatonomy method outcomes for the case studies of self-monitoring rearing tanks and autonomous tank operations will be presented. More exhaustive presentations of these results can be found in Eilertsen et al. (2021).

5.1 Self-monitoring rearing tanks

Table 2 outlines the stages adapted on this analysis collectively. The presented data in Table 2 are based on the assumption that installation and design only takes place once, sensor calibration and cleaning are executed periodically and the rest of the listed stages are executed continuously.

The study showed that the overall system should be able to monitor all aspects of production (i.e., population/individual, water quality, and equipment parameters) on a continuous basis. Moreover, the system should automate sensor maintenance and calibration as this will reduce personnel workload and secure high quality and reliable data. The sensor and equipment used would also need to be suited for long-term deployment in the given conditions, and a degree of redundancy in sensors should also be realized. All data gathered from the sensors need to be time-synchronized and have sufficient coverage of the tank volume to allow for comparisons and combinations of parameters across time intervals and space. A control station where the data is processed, analyzed and visualized for personnel should also be a part of the overall system design and implementation. Data should be stored both locally near the control station and in a cloud-based



(a) Manual dead fish removal

(b) Autonomous dead fish removal

Fig. 7. Illustration of dead fish removal process in land-based production units (Illustration by Mats Aarsland Mulelid).

Table 2. Stages that need to be completed in order to realize self-monitoring rearing tanks system.

Stages	**Descriptions**
Stage 1: Design and install sensor system	Sensors needs to be chosen and installed for measuring all aspects of water quality at the optimal position within the tank and the system as a whole. This includes, e.g., sensors to monitor the usage of power and water quality (such as, e.g., temperature, pH), light levels within the facility, etc. Cameras need to be installed both on the surface and submerged in the environment to monitor the population. A system to monitor the equipment must also be implemented. Sensor fusion, sensor data reliability and redundancy of the system should be guaranteed.
Stage 2: Calibration	Sensor should be self-calibrated. The autonomous system will take into account each sensor types specific calibration needs (e.g., calibration frequency). This includes the use of necessary auxiliary sensors and reference mediums.
Stage 3: Data capture	Capture high quality synchronized data from all sensors. The sampling rate needs to be fast enough to catch the fastest changing variable.
Stage 4: Data transfer	Captured data is transferred to a control station for processing, and to a cloud solution for long term storage. Accessibility of the obtained data should be guaranteed at all times.
Stage 5: Data processing	Data should be processed using advanced algorithms such as machine learning techniques.
Stage 6: Data visualization	Data need to be visualized for personnel review. This includes highlighting interesting aspects of the raw and processed data.
Stage 7: Data review	Data shall be reviewed by personnel who judge facility status, operation security, and progress. This also includes a decision support system in order to assist personnel in any decision making.
Stage 8: Sensor maintenance	Sensors should be cleaned and disinfected regularly to provide accurate information using an autonomous system and secure potential disease spread. Trained personnel will at times be needed in order to change worn sensors or parts.

solution to facilitate both flexibility of use and redundancy in storage. The system should be able to analyze trends, make predictions and estimates based on the collected data, thereby increasing their utility in daily farm management. Furthermore, the system should visualize and present data and information to the personnel in an intuitive manner, and personnel should be able to manually access all data they desired. Based on the collected and derived data, the system could ultimately provide decision support for personnel based on situational and historical data analysis, and provide advice on the optimal time to execute operations related to production. This will lead to 24/7 objective and optimized monitoring and inspection of the full facility and pioneer the realization of I4.0 principles in land-based production units.

Although the most optimal design for such a system would be one where all the relevant sensors are fully integrated, this may be a costly solution that is not feasible for facilities that are already built. An alternative solution could be to combine integrated sensors and automated laboratory stations from different providers and producers in a common system. This could be realized as a single unit deployed at single tanks, or a more modular system that could be shared between rearing tanks. Moving the modular system between rearing tanks could either be done by some auxiliary system, or the package itself could be designed with this in mind and be self-propelled and capable of moving between rearing tanks on its own.

5.2 Autonomous Tanks Operations

Table 3 shows the outcome of the analysis of the autonomous tank operations case study, the different stages being generalized to account for all the key operations expected at tanks.

Although an autonomous tank operation system would not necessarily need to complete these operations simultaneously, it will need to be able to do so in quick succession (i.e., move from tank cleaning to removing dead fish without much delay) and in accordance with the production plan. The system also needs to be able to decide in which order the operations should be completed if they are all deemed necessary at the same time. Irrespective of the type of operation, the system would need components to facilitate perception, interpretation of observations, and manipulation/intervention.

To enable autonomous feeding operations, the perception system should provide video or other sources of data describing the behavior and size of the fish, and the feed silo capacity and level must be self-monitoring. For cleaning operations it is critical that the perception system provides images of the tank wall/bottom, while dead fish removal requires a system able to identify dead fish at the surface, inside the tank, or at the bottom.

The system should further be able to infer higher level information by interpreting these data. For instance, in feeding scenarios, the system should be able to detect when the fish are hungry based on behavioral observations (appetite response), and autonomously decide the type and size of the feed suitable for the tank population based on fish size. The system should further identify where to distribute the feed to ensure an optimal feeding session once feeding is initiated, and adjust/terminate feeding when the fish stop feeding (as observed through behavior or buildup of uneaten pellets at the tank bottom). In cleaning operations, the system would need to identify if cleaning is necessary based on perception data, and should be able to evaluate the outcome after completion. Finally, in case of dead fish removal, the system should provide an analysis of the potential cause of death, and keep track of the number of dead individuals from each tank.

The main intervention tool required for feeding operations would be a device for delivering feed to the tanks. If specialized feed is required, the system should also be able to accommodate for this. The amount of feed distributed per session should also be logged and stored to monitor growth and feed conversion ratio. For tank cleaning, intervention tools would be required to clean the tank wall and any other surface of interest, and the process should also be initiated autonomously (e.g., depending on the estimated need for cleaning or as part of a periodic cleaning plan), regardless of whether the tank is occupied or empty. The system should further gather up any waste particles while cleaning unless cleaning is done frequently enough to reduce the amount of waste to a level manageable by the natural circulation within the tank. The cleaning system should also be able to clean auxiliary aspects connected to the tank, such as pipes, valves and filters. For the dead fish removal case, the main tool for intervention could be a manipulator able to grasp the dead fish once detected, a process that should be done rapidly to prevent the dead fish from affecting the tank environment negatively.

All these operations need to be possible to initialize and supervise from a central control room from which personnel can initiate, monitor, and cancel operations. This control room should also enable personnel to take manual control over the operation in cases of emergency, and data on the operation status and progress should be presented to personnel at all times. All data, information, and logs related to operations conducted using autonomous tank operations should further be stored and used as historical data for decision support systems and future production planning, and to maintain operational histories in individual portfolios for each population.

Autonomous tank operations require mechanical moving parts and, thus, the system for realizing these must also take proper safety precautions into consideration. This includes self-localization and situational awareness for any robotic limbs or other moving parts, and collision avoidance systems to avoid causing damages, as well as emergency shutdown protocols.

While there exist feed spreaders that are already highly mechanized and automated, these would have to be expanded with capabilities for perceiving fish appetite and refilling the dispenser to fulfill the aim of fully autonomous feeding. Regarding tank cleaning, there exist several solutions that could be useful as a basis, either for systems integrated into each tank or self-propelled systems capable of moving between tanks. Removing dead fish from the tank environment would likely entail a water-proof robotic gripper system able to gently but firmly remove the fish. While there exist commercial robot manipulators suitable for this, they are often relatively short, meaning that a solution for this purpose would either depend on some sort of self-propelled system either in the form of an underwater vehicle or a rail-mounted robotic unit.

While the three operations described above have differing goals they share some similarities, and it is possible to imagine systems able to handle several different tank operations. One approach to this could be a self-propelled robotic caretaker with the ability to exchange its end effector tool to suit the given operation. This could be a cost efficient solution that is easy to integrate into existing facilities, as well as newer facilities, and could be set up to do both cleaning and dead fish removal. Such a system would also be easily scalable, as one could simply integrate multiple systems and give each a sector of responsibility within the facility. On the other hand, feeding occurs frequently during production and is less dependent on movement within the facility. Thus, it is possible that combining a separate system for feeding with an autonomous system for the other tank operations. This would provide a holistic solution that may provide substantial relief on employee workload and move the industry more towards an autonomous future.

Table 3. Stages that need to be completed in order to achieve autonomous tank operations

Stages	Descriptions
Stage 1: Identify operation necessity	The monitoring system should be developed to identify whether a certain operation must be performed, and a signal should be sent to the mission planning system to plan and execute tasks needed to achieve the given operation.
Stage 2: Deploy system	The system should be deployed to the given tank autonomously and the operation is initiated.
Stage 3: Execute task	The mission planning system plans the tasks to be executed autonomously. Mission planning requires self-localization and situational awareness, and must incorporate a collision avoidance system to avoid damaging humans, fish, the tank and other infrastructure. The robot must execute the planned task and respect the requirements of the planning system. The system must run self-diagnostics in the event of system errors and must respect properly defined safety margins. Personnel, as super-user, has the option to intervene with the operation.
Stage 4: Monitor and display progress	The progress of the operation should be displayed for personnel at a control center. Personnel can also view video feed of ongoing the operation. Progress should be displayed from different operations in control room and alarm systems should take into account information from the overall system design of the whole facility and available sensor data.
Stage 5: Store and communicate operation variables	The system should store important variables and communicate with the monitoring system to help track population numbers, movement and operational history. Accomplished, pauser, stopped or postponed missions should be reported. Logs from missions should be stored and utilized for future planning.
Stage 6: Wait for confirmation and new orders	Once the operation is finished the system stops and waits for confirmation from personnel or goes back to stand-by mode. Depending on the specific operation, the personnel has the option of redoing the operation if the results are not satisfactory.
Stage 7: Necessary maintenance between operations	After receiving new orders, (e.g., move to the next operation or enter standby mode), the system should run a self-diagnostic to check if all part are functioning. The system then needs to report on the self-diagnostics and require maintenance if necessary. Finally, the system must be disinfected after every operation to prevent disease spread between tank populations.

6. CONCLUSIONS AND FUTURE RESEARCH

This article highlights some of the major challenges in modern smolt production and outlines a path forward that will move it into the Industry 4.0 (I4.0) paradigm and that is aligned with the industrial needs. This has been achieved by first studying the current state of the art of smolt production and typical operations conducted at smolt production facilities. The principles of I4.0 were then presented, followed by evaluations on the potential of applying these to the operations in smolt facilities. Some of the most important operations at smolt facilities have been studied in greater detail, with emphasis on challenges, research needs, and potential solutions. Three case studies, i.e., self-monitoring rearing tanks, autonomous tank operations, and Smolt 4.0: Optimized smolt production, have been used to demonstrate how research needs can be used as a basis for deriving concrete industrial applications. Based on the case studies, an extensive analysis was conducted to determine specifications and requirements for realizing the Smolt 4.0 concept.

DECLARATION OF COMPETING INTERESTS

The authors have no conflicts of interest related to the work presented in this article.

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