Project title:	Limitations to implementing robotics in UK ornamental horticulture
Project number:	AHDB scoping project (P1909317)
Project leader:	Dr. Alan Millard, University of Plymouth (currently at University of Lincoln) Dr. Martin Stoelen, University of Plymouth (currently at Western Norway University of Applied Sciences)
Report:	Final report, May 2021
Previous report:	n/a
Key staff:	Prof. Mick Fuller Benjamin Green Oksana Hagen Dr. Frederico Belmonte Klein
Location of project:	Plymouth, UK
Industry Representative:	n/a
Date project commenced:	1st December 2019
Date project completed (or expected completion date):	31st March 2020

DISCLAIMER

AUTHENTICATION

We declare that this work was done under our supervision according to the procedures described herein and that the report represents a true and accurate record of the results obtained.

Alan Millard

Senior Lecturer

University of Lincoln

Signature .... Date ....11/03/2021..........

Martin F. Stoelen

Lecturer in Robotics

University of Plymouth

Signature .... Date ....11/03/2021..........

Report authorised by:

[Name]

[Position]

[Organisation]

Signature .... Date ....

[Name]

[Position]

[Organisation]

Signature ....   Date ....

CONTENTS

GROWER SUMMARY

Headline

There are challenges in implementing robotics in UK ornamental horticulture, in particular due to the large variability in plant species and varieties. However, there are also automation opportunities that can help make growers more competitive in the near term, and there is scope for customised innovations leading into the future.

Background

As with the rest of the UK horticultural sector, the production of ornamentals is heavily dependent on manual labour. This manual labour is typically imported, as it is in most western European countries, from eastern Europe, Asia, and Africa. Growers thus rely upon the availability of such imported labour at a reasonable cost. This availability depends on complex financial (e.g. minimum salary, salary competition with other industries), personal (e.g. attractiveness of the local amenities, availability for seasonal labour), and political factors (e.g. availability of visas, exchange rates).

Robotics and automation are increasingly being suggested as a means to help resolve manual labour issues in agriculture in general (Bac et al., 2014) (Duckett et al., 2018). That is, to assist with traditionally human-centred operations where perception, decision making, and dexterity are required. For example, harvesting, pruning, precision spraying, and transportation operations could be partially or fully automated to alleviate a grower's reliance on manual labour. Building on the AHDB project GROWBOT (Sena & Howard, 2020), this report aimed to identify remaining issues in the uptake of robotic technology for ornamentals, and to identify potential ways of resolving them.

Summary

The main scope of this study was to investigate the remaining barriers for automation of agricultural tasks in the ornamental sector in the UK. It should be noted that the authors of this report are researchers in the cross-section of robotics, machine learning and sensors applied to agriculture, and the report should therefore be taken with this perspective in mind. Further work exploring simpler mechanical solutions, and going more in depth on machines that do not use sensory feedback to operate, is likely needed. This report focuses on cut stem grower, plug plant growers, and nurseries. It attempts to document the current procedure for each production step, to highlight the most important challenges, and opportunities, for automation, and in this way serve as a piece in the puzzle for gradually increasing the level of automation for these producers. We hope the report can be useful for end-users, academics working on technical solutions for agriculture, and technology providers interested in developing products for this application of automation and robotics.

Most robotic solutions will normally apply to single plant species, i.e. plant types with defined morphological characteristics that the robot can be programmed and fine-tuned for. Taking that robotic system and applying it to another plant species with a different morphology and requirements would mean re-programming and obtaining new datasets. Simpler automated solutions, like conveyor belt systems, also require considerable scales of operation to make the investment worthwhile. However, there are specific challenges that can likely be met by increased automation in the near future.

As explored in the previous AHDB GROWBOT project (Sena, 2019), robot learning can help target low batch-size tasks for ornamentals. In addition we believe there are specific opportunities for each type of grower that should be explored as a priority. For example, the counting and grading of cut stem flowers, where there is automated machinery available for flowers with a higher price-point, but where lower-cost/smaller-scale solutions based on off-the-shelf robot arms, soft grippers and machine learning may be feasible in the medium-term. However, targeted RD&I projects with a relevant technology provider are needed to integrate and bring such robotic solutions to working prototypes, and ultimately to market.

Similarly, the grading of plug plants may be possible, where the large variety of different plants to grade may be overcome by generating the data sets required for machine learning on-the-job by current skilled staff during a transition period. Or, the application of mobile robots for addressing gapping in nursery plant stock. Here solutions are available on the market, but may at the moment be difficult to justify in terms of cost for smaller operations. Wider adoption and larger-scale production may help bring the price point down for such systems.

There are commonalities to some of the challenges that may be exploited in making cross-grower solutions with bigger potential markets. For example moving, and grading, plants. This would require resolving the issues related to handling a wide enough array of different plants, but the flexibility offered by light industrial arms, soft grippers, and machine learning is promising. More work is needed to explore these opportunities, and to ensure the solutions proposed are grounded in the needs of the growers, both practically and financially.

Financial Benefits

Increased automation can likely provide cost savings for UK growers of ornamentals, but needs to be tailored to the scale of operation, and varieties of plants grown. Given the difficulties in obtaining, and high cost associated with, imported skilled manual labour, automation can also help increase predictability of operations.

Action Points

- Explore opportunities for working with research partners and technology providers to customise technology to needs, for example through Innovate UK funding
- Help foster, and work with, robotics research initiatives to identify and solve tasks specific to ornamental plants culture
- Consider the full system-of-systems when optimising operations for automation/robotics, for example by merging tasks
- Reduce variability of the environments and tasks, for example the number of different sizes of trays or pots, which can facilitate the deployment of traditional automation, machine learning solutions, and autonomous robots
- Avoid cramped spaces: High space utilization can sometimes make robot navigation and grasping tasks more complex

SCIENCE SECTION

Introduction

This scoping project was launched to help understand automation issues in the context of the ornamental sector in the UK. The principal objectives were:

Objective 1: Identify and explore issues limiting uptake of automation and robotics by the horticultural industry. While the focus should be on the ornamentals sector, relevant issues from other horticultural production systems would be welcomed.

Objective 2: Identify potential solutions to these issues, including any relevant case studies.

Objective 3: Include feedback from growers about what they perceive to be the best use for a robotic arm or other robotic solutions on their sites.

The materials and methods used will be described, before results, discussion and conclusions are presented.

Materials and methods

This project was to run for 12 weeks from November 2019 to January 2020, comprising the following work packages that directly address the above objectives and deliverables:

Work Package 1: Work with local growers to determine the barriers to adopting robotic automation in the ornamental horticulture sector **(6 weeks)**

Work Package 2: Identify potential solutions to uptake issues, with specific case studies from Kernock Park Plants **(6 weeks)**

Work Package 3: Develop questionnaire on robot usage, limitations, and potential for national producers **(6 weeks)**

Work Package 4: Final report evidence collection, data analysis, and writing **(8 weeks)**

Due to administrative delays, the project started on 1st December 2019, and was originally due to end in February 2020, but a 1-month no-cost extension was granted to complete further site visits. All site visits were successfully completed before lockdown restrictions were enforced in the UK, however the impact of the COVID-19 pandemic resulted in a delay of the final completion of the report.

The work was carried out by two Research Fellows (Frederico Klein and Oksana Hagen) and a Research Assistant (Benjamin Green). All were employed part-time at the University of Plymouth, under the supervision of Dr Alan Millard, with input from Dr Martin Stoelen and Professor Mick Fuller.

The project method included telephone interviews and site visits to growers across the UK, but focused on the Southwest. The visits were intended to identify labour-intensive operations that are most amenable to robotic automation, and explore issues that may be limiting the uptake of such solutions (e.g. cost of ownership / service models, safety of working in close proximity to humans, variation within/between product lines or growing environments, or time taken to train a robot). A combination of staff from the project team took part in the visits, and documented with interviews, images and videos. The 8 visits are described briefly below, and see Figure 1 for a map of the visits.

Table 1. List of sites visited, type, date and team.

Facility Visited	Type	Date	Researcher Team
Kernock Park Plants	Propagating nursery	17th Dec 2019	Prof. Mick Fuller Dr. Alan Millard Dr. Frederico Klein Benjamin Green
Fentongollan Farm	Cut stem and plug plant grower	12th Feb 2020	Dr. Alan Millard Oksana Hagen Benjamin Green
Darby Nursery Stock	Nursery stock	25th Feb 2020	Dr. Alan Millard
Scented Narcissi	Cut stem grower	2nd Mar 2020	Oksana Hagen Benjamin Green
Scilly Flowers	Cut stem grower	3rd Mar 2020	Oksana Hagen Benjamin Green
Double H Nursery	High-value ornamentals	4th Mar 2020	Dr. Alan Millard
Johnsons of Whixley	Nursery stock	6th Mar 2020	Dr. Alan Millard
Kernow Alstroemeria	Cut stem grower	13th Mar 2020	Dr. Alan Millard Oksana Hagen Benjamin Green

Based on the visits and interviews a national survey was drafted. This survey aimed to explore the robot usage, limitations, and potential nationally in ornamentals. The survey questions are included in Appendix A. Unfortunately, the survey was not distributed to growers during this project due to unforeseen circumstances. We hope it can still form the basis of a future national survey for informing the AHDB, growers, technologists and policymakers.

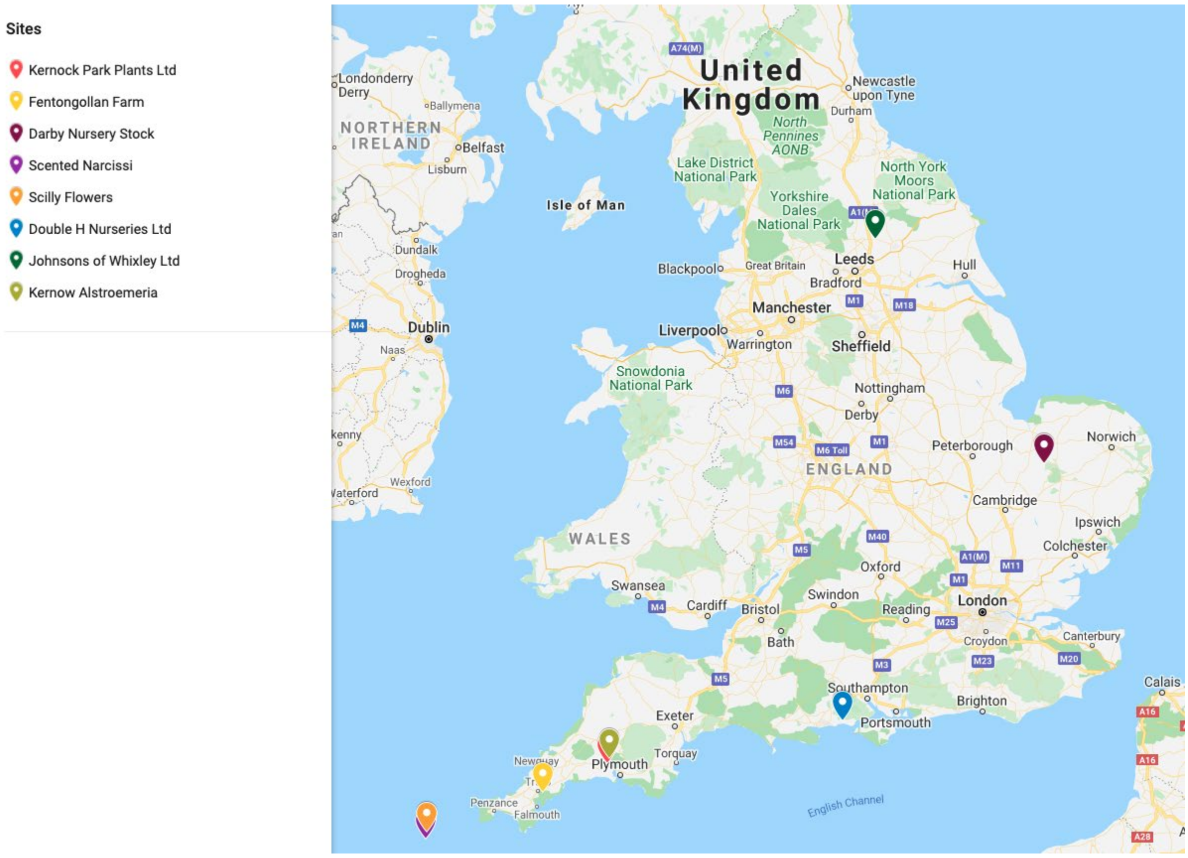


Figure 1. Map showing sites visited during the scoping project.

Results

Visit 1: Kernock Park Plants (17th December 2019)

Kernock Park Plants is a propagating nursery, of which there are around 20 in the UK. The company employs a variable number of staff throughout the year, but is usually between 50-100. On their site they have more than thirteen million plants of 1,200 different varieties; smaller growers, however, can have even greater variety of crops. See Figure 2.

a) Typical greenhouse with multiple varieties grown together.

b) Space optimised for the movement of staff - narrow corridors.

Figure 2. Kernock Park Plants visit on the 17th of December 2019.

The business is a primary producer that propagates plug plants using cuttings, either cut from their own mother stock, or imported from other countries - very few are grown from seed. The cuttings are manually inserted into plastic trays of plugs by human workers, and then grown indoors until they are mature enough to sell on. See Figure 3.

a) Manually transplanting cuttings into trays of soil plugs.

b) Trays of transplanted cuttings grown into mature plug plants ready for grading and sale.

Figure 3. The process cuttings go through at Kernock Park Plants before being sold as plug plants.

Once the plug plants have sufficiently matured, each tray of plants is graded - dead or dying plants are removed, and the rest are sorted into categories by size (e.g. small, medium, and large). The resulting trays of uniformly sized plants are then sold on to nurseries or garden centres, who grow the plug plants further to add value for the end consumer. Barcode labels are used to track each tray, and maintain a system for monitoring inventory levels and forecasting ordering patterns.

According to our contact Bruce Harnett, existing automated solutions have many limitations with diminishing returns to growers (e.g. machines for transplanting cuttings). Moreover, automation imposes limitations on how to grow and breed plants - currently their space is optimised for manual labourers, who often work in tight spaces with high variability of tasks. This dictates a certain need for flexibility in any machinery used. In addition, the smaller the business, the more general the proposed solution needs to be: it is not an option to use complex equipment to solve single tasks, as economy of scale does not apply. A high number of tasks impose additional limitations, such as physical space (which often can't be altered). In Kernock's case, the site being on a hill is an issue for movement of plants and equipment between greenhouses.

Visit 2: Scented Narcissi (2nd March 2020)

During our visit to the Scented Narcissi growers on the Isles of Scilly in Cornwall, we were given tours of several farms on the islands. It was evident that the handling of these flowers is a very labour intensive process.

Grown in small bays, the flowers are arranged in rows with paths between them just wide enough for workers to move along. See Figure 4. The width of the rows varied by farm, sometimes up to four feet wide. In some circumstances the workers could only reach the near side of the dense and tall foliage. The terrain is also hilly and tricky to traverse.

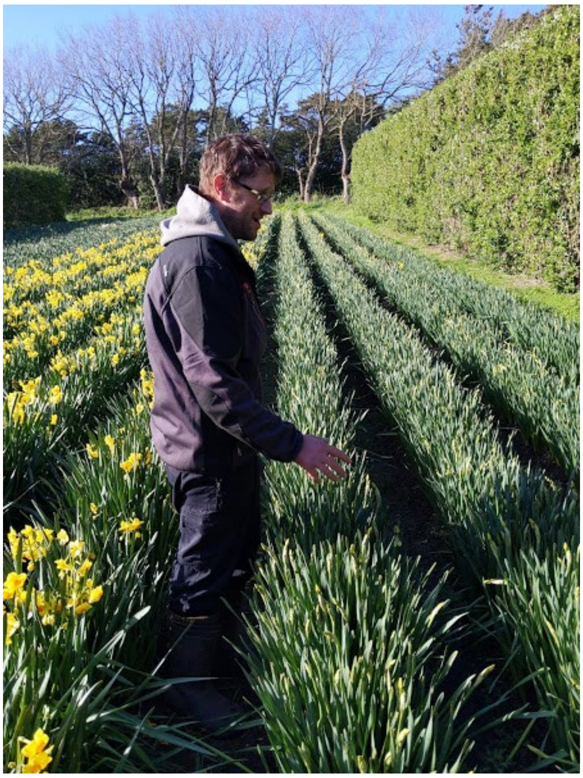


Figure 4. Scented Narcissi grower visits on the Isles of Scilly (2nd of March 2020).

Upon picking bunches of approximately one hundred flower stems, the banded bundle is then transported to a nearby sorting facility. Elastic bands are used for bunching in the field. As the flowers with the longest stems fetch a higher market value, they are graded by length into multiple grades in 5 cm increments. The measurement is performed manually by using a grading board with horizontal planks that signify a certain length of the stem (see Figure 5a). The process is not complicated, but to perform it efficiently, one needs a certain amount of experience. Some of the growers are attempting to automate the process by using essentially the same grading apparatus and slightly shaking the stems until the ones of the correct length fall through. See Figure 5b. However, this innovation does not yet work reliably enough to be used.

a) A typical grading board for stems.

b) Prototype automatic grading machine.

Figure 5. Two approaches for grading of stems.

The graded stems are then transported to the central handling facility where the final packaging of stems from all farms is performed and subsequently shipped out by airplane to the mainland. In the handling facility, the stems are being counted manually into small bunches and then automatically wrapped in a rubber band on a conveyor belt, as shown in Figure 6.

Figure 6. Bunching of stems.

The main challenges for handling narcissi soft stems are their fragility, and their low cost. There is a delicate balance between being careful and being efficient, and this requires different solutions, as compared to more robust plants such as roses.

Picking the flowers is a very laborious process - the worker must find the stem with buds of a particular level of maturity, and then reach down to its base to pick it. There is a lot of foliage present that could hinder automation of this task.

Visit 3: Kernow Alstroemeria (13th March 2020)

Kernow Alstroemeria is one of the largest producers of alstroemerias in Europe. The production scale is about 3.5 - 4 million stems per year. All of the growing is done in greenhouses under highly controlled conditions.

The main limiting issue for the grower seems to be labour costs and availability of seasonal workers. Currently the grower employs a few experienced non-UK seasonal flower pickers that come back every season for many years, but this could become more difficult due to Brexit and the COVID-19 pandemic.

The plants are graded into three categories based on growth, at the point of picking - the flower pickers would estimate the length of the stem before removing the flower, thus obtaining a bunch of a single grade. Alstroemerias do not have a single flower bud, like narcissi, thus the grading process requires less precision, unlike, for example, narcissi, that all should have very precise length. Also, the entire stem is easily plucked from the ground by gripping the top of the stem, unlike the narcissi, where it is absolutely necessary to reach down to the bottom of the stem. See Figure 7. This could perhaps make it more amenable to automation/robotic solutions in the future.

a) The growing conditions.

b) The bunching conveyor belt.

c) Flowers after picking and grading.

d) Flowers prepared for shipping.

Figure 7. Kernow Alstroemeria visit on 13th of March 2020.

Packing alstroemerias is a laborious process done by hand mostly with the assistance of the bunching conveyor belt. Some parts of the packing and handling were automated, such as tying the bunches together, while others were manual, like wrapping the bunches in paper. The grower was aware of existing fully automated systems, but current solutions don’t make financial sense for the scale of their business. One example of a grading and bunching solution for the alstroemerias would be the system proposed by the Dutch company Havatek (Nieuw-Vennep, Holland). The flowers are fed one-by-one into the machine on one side and exit the machine on the other side sorted by length and stem thickness, bunched in the preset number of stems. This solution is based on computer vision and mechanical operations, however it would require significant investment and space for the grower. This machine is priced at around 250,000 Euros.

Visit 4: Fentongollan Farm (12th February 2020)

The farm is a large producer of both daffodils (flowers and bulbs) and plug plants. The biggest challenge for this grower is labour costs - the labour is highly seasonal, depending on the market demands. The demand from January to April can reach 4000-5000 trays per week, but from June to July it can be as low as 1000 trays per week. Labour constitutes around 50% of the overall costs.

At its peak, the grower employs 40-50 pickers for the daffodils. The main difficulty for the picking of the daffodils lies in the expertise. The flower must be in a specific stage, looking like a pencil, with no yellow visible. Bunching of the daffodils is done in the field, unlike in other stem flower growers. The picking work is strenuous, and is performed outdoors in all weather. Imported seasonal labour is the only option at the moment[1].

In addition to cut-stem daffodils, the company grows plug plants from seed. Seedling production is characterised by high variability - there are around 100 species of plants being grown at the nursery. The process of sowing the seeds is highly automated with machinery. It consists of filling the plug-trays with compost, creating dimples in the compost, and then pumping seeds into them under pressure. A supervisor ensures that the correct variety is being seeded, and the correct amount of trays is sown. By contrast, the labelling process is currently manual.

The trays of seedlings have to be transported either to an outside space or polytunnels to be grown-on. In the polytunnels, the trays are elevated to improve air circulation, by placing them on a layer of upturned plastic plant pots. See Figure 8. Positioning of the pots, and subsequently placing the trays on top, is a very laborious task. Since positioning of the pots and trays is done in a highly controlled environment, this task seems amenable to automation.

[1] https://www.theguardian.com/environment/2021/mar/07/bloom-time-my-day-picking-daffodils-against-the-clock

a) Automatic preparation of the seedling trays.

b) The seedlings trays positioned on the plastic pots in the tunnel to aid aeration.

c) Seedlings are growing in a protected environment.

d) Daffodil bunches prepared for shipping to the customers.

Figure 8. Fentongollan visit on 12th of February 2020.

Visit 5: Scilly Flowers (3rd March 2020)

Scilly Flowers (also on the Isles of Scilly), produces carnations in addition to narcissi. Because the soil composition on the island is not ideal for growing carnations, they are grown in a protected environment, in containers.

This presents an interesting case about managing the watering of the containers. A standard conductivity sensor could be used, see Figure 9. However, it becomes difficult, if you have many containers in place, to manually probe each container. Another complication is that different varieties have different nutrition requirements. This suggests a connected automated monitoring and watering system that would connect the sensors from each of the containers to the centralised server. This could be a good and simple case of the potential for automation. As in the other cases considered in this report, the current solutions that address this problem are costly, with each sensor priced more than £100, which seems infeasible if needing one in every container. The grower has shared with us his plans of building a custom system based on Arduino, but mentioned that he lacks the technical expertise to do it on his own. This could be a great opportunity for industry/academic collaboration, as building a system like this is within the reach of a student project.

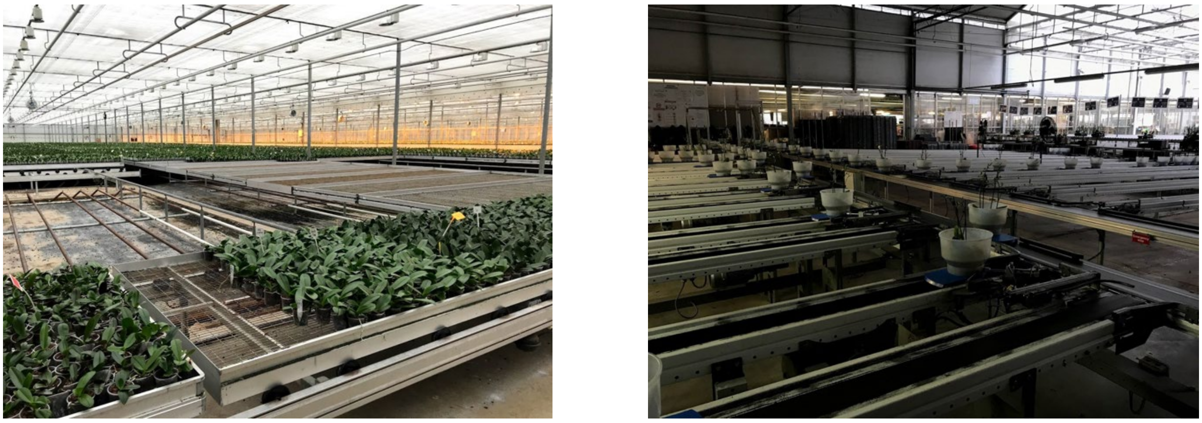
a) The growing conditions of carnations. b) Conductivity sensor used.

Figure 9. Scilly Flowers visit on the 3rd March 2020.

Visit 6: Double H Nursery (4th March 2020)

Double H Nursery are a producer of ornamentals in the South of England who focus their business predominantly on growing houseplants for sale direct to supermarkets, growing roughly 4.5 million plants a year. During this visit, we focussed on their orchid growing facilities, although the grower also specialises in chrysanthemums and roses. In this facility, orchids are grown, packed in “presentation pots”, and wrapped for final sale on supermarket shelves.

The grower uses an approach to automation and growing based on practices that are commonplace in large-scale ornamental production in the Netherlands - the business focuses largely on orchids, with the only variance being colour or variety of the orchid. The plants are grown in large glasshouses with sophisticated climate control to maintain optimal growing conditions throughout the year.



a) Grid system of modular trays which move on rails.

b) Automated conveyor belt system for moving the potted orchids.

Figure 10. Orchids grown in large climate-controlled glasshouses at Double H Nursery.

The glasshouses contain a system of modular trays arranged in a grid, which are moved on rails as seen in Figure 10a. The trays are moved from one end of the greenhouse to the other as the plants mature through the stages of their growing cycle. The greenhouses use an automated overhead sprinkler system for watering, and the grower has invested in an intelligent potting machine. There is also an automated conveyor belt system for moving the potted orchids around the site, see Figure 10b.

The main area of interest for the grower in terms of additional automation revolves around the final packing process, in which the orchids are prepared for sale to supermarkets. This stage involves placing the potted orchids into “presentation pots”, and wrapping them in plastic ready for supermarket shelves. Currently, this is a largely manual process, but there are some opportunities for automation here - for example, a commercial off-the-shelf robot arm could be programmed to transfer potted orchids from conveyor belts into presentation pots.

Visits 7 and 8: Darby Nursery Stock (25th February 2020) and Johnsons of Whixley (6th March 2020)

Darby Nursery Stock and Johnsons of Whixley are similar growers specialising in selling stock for sale in garden centres, and have vast varieties of plants grown on site. There are large greenhouses on site, as well as large outdoor growing areas where plants are finished ready for sale. Johnsons of Whixley supply around six million plants and trees every year, in both wholesale and garden centre markets, and have a seasonal workforce of an additional 30-50 workers each year.

For both of these growers, one of the primary barriers to automation is in the range of plants that they grow. There are vast differences in size, foliage, height, and weight of plants, from grasses to succulents to trees. This large variation poses significant challenges for automation, particularly in combination with the irregular layout and uneven terrain of large, predominantly outdoor sites.

Both growers use trolley systems for moving and packing plants. These trolleys are a standardised product that is used widely across the industry, with shelves that are configurable for different heights of plants. See Figure 11 for an example. The shelves are largely packed by human workers, who must assess plant heights and pack the plants on the appropriate shelves.

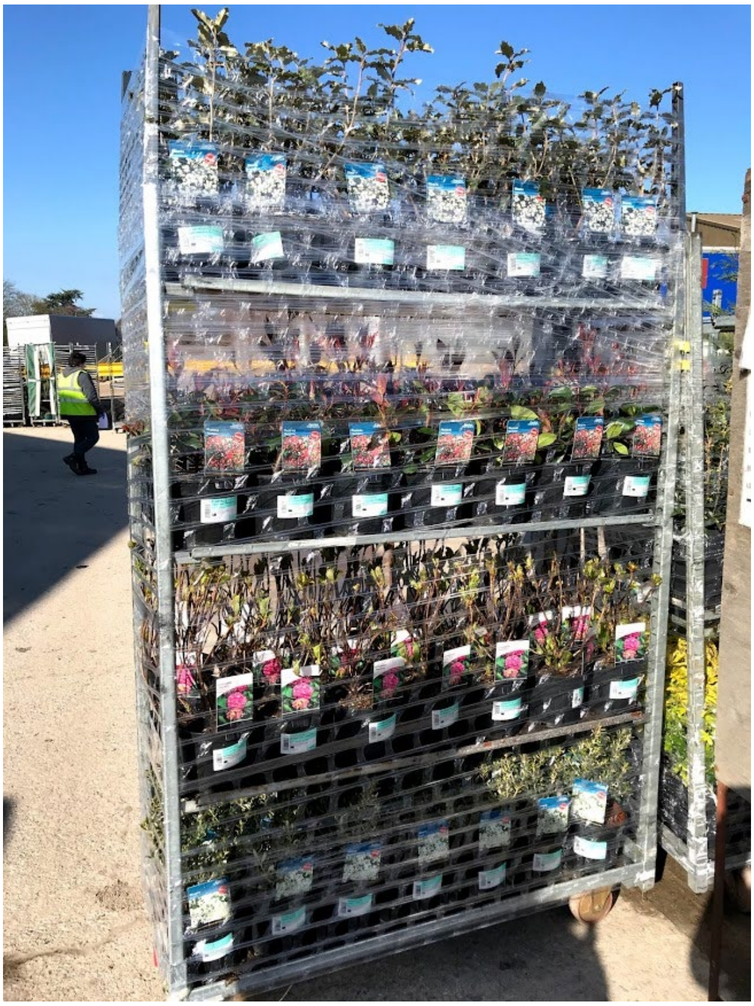


Figure 11. An example of plants packed onto a trolley with customisable shelf heights (Johnsons of Whixley).

One of the main problems encountered by Darby Nursery Stock was issues with gapping in their plant stock. When plants are picked to fulfill an order, this leaves gaps in the arrangement of plants (see Figure 12), so to optimise space on site, a human worker is then required to reorganise the remaining plants to fill in the gaps. This is a slow and laborious process, which is ripe for automation - examples from the USA and Canada of small robots that can pick up plant pots and place them down again are one such solution. See Figure 13 for two examples. The main limitation to the actual adoption of such robots is the commercial price. As an example, the HV-100 from Harvest Automation is available at the price of $130,000 for a team of four robots to purchase, or to rent for $30,000/3 months, which may be prohibitively expensive for some growers.

Figure 12. Gaps left by removing stock for order fulfillment at Darby Nursery Stock.

a) Mobile HV-100 robot available from Harvest Automation (Massachusetts, USA).

b) BigTop robot, Advanced Intelligent Systems (Burnaby, Canada).

Figure 13. Two example robots available/near market for picking and placing pots.

There are some elements of site infrastructure that would not benefit from further automation, as efficient solutions are already in place. This includes irrigation, with solutions for this including underground irrigation which feeds up into the medium above, and overhead sprinkler systems. Transportation around the wider sites is also not an issue for either grower

- due to the uneven terrain and multiple sites at Johnsons of Whixley, movement around the site is largely facilitated by car, and there are wide avenues in their growing environments which are suitable for this. At Darby Nursery Stock, small tractors and trailers are used to move plants around, providing an efficient system for transporting large numbers of plants with relatively little human labour involved.

Discussion

Throughout the visits, we have observed many different operations performed for growing and handling ornamentals. These have varied based on the scale of the grower and the variety of plants involved in their businesses, and the central aims of their growing operations. In this section we have grouped the growers into three main categories: cut-stem, plug plants, and nursery stock. For each of the three categories of growers we have tried to identify the main tasks. We then estimate the potential of automation and robotic solutions in aiding these tasks, and identify some of the challenges for the commercial implementation of such technology.

Findings for cut-stem flower growers

The main tasks for handling cut-stem flowers are similar for most of the growers:

- Picking
- Bunching
- Grading
- Counting
- Packing
- Growth monitoring.

Some of these steps could be combined and/or reordered, as observed on site visits. For example, grading and picking is done simultaneously for alstroemerias. The different tasks are discussed below:

Task 1: Picking. Picking is both laborious and strenuous, and often represents a high share of the growers' cost in horticulture in general. However, it is unlikely that an affordable automated solution to picking flowers will be available on the market in the short-term, due to challenges associated with traversing uneven terrain, complicated perception/occlusion, and control problems. The fundamental technologies required to develop a selective picking system already exist, particularly for the flowers that are easier to detect and to pick (like alstroemerias and carnations), however, the financial investment required to get it to market is likely to be significant. Such solutions would benefit from the recent advances in machine vision applied to agriculture (Bac et al., 2014) (Klein et al., 2019), and could potentially use soft gripping technology (Mohamed et al., 2019), but most of the solutions for selective harvesting of other crops are still at a pre-commercial stage (Duckett, et al., 2018). A thorough financial review would also be needed, to compare the market for selective and robotic picking of flowers with for example fruits and berries.

Task 2: Bunching. We observed that growers who operated at a larger scale had already invested in bunching machines based on a conveyor belt. Some outsourced the counting, bunching and packaging to a central processing plant, where the level of automation is higher. This model is actually quite efficient, since the influx of flowers to a central processing plant is more stable throughout the year, and so they are able to hire staff on a permanent basis and invest in more automation.

Task 3: Grading. Even if right now done by hand, grading is the task that seems to be the most ripe for automating for stem flower growers. Grading can be performed in a controlled environment, and is very well structured as a task. There is potential for 2D/3D cameras and algorithms to be used for grading by length. Whether an actual robot is necessary, or a simple mechanical solution is sufficient would be up for a further investigation and prototyping. However, the grading process, because of its structure and controllability is a good example of a task that is amenable to automation. Unfortunately, the growers do not typically have the expertise to build these systems themselves, and would need an off-the-shelf industrial solution. There are industrial solutions that work well for larger scale operations, Havantek (Nieuw-Vennep, Holland) have developed approaches using both x-ray and camera systems. In the literature, previous work on stereo vision sensors and template-based Computer Vision for grading Anthurium flowers showed good correlation with manual grading (Hemming, Pekkeriet, and Van Der Schoor, 2010), while more recently Deep Learning approaches has shown promise for automated grading of Oncidium Orchid cut flowers (Te Tsai, 2019).

Task 4: Counting. Counting is a task identified by some of the growers to be difficult. The task is important, since the flowers are sold per stem, any mistakes result in customer dissatisfaction or loss of revenue. It is done manually at all the farms we have seen, and the manual process included the workers picking a handful of flowers from a large graded bunch and then visually estimating 5 flowers to combine into the bunches of the required size. While being physically undemanding, the task requires precision and prolonged attention. Because of its repetitiveness, the workers inevitably would make mistakes. This task could be automated in many ways, starting from mechanical solutions to using the soft robotic arms together with a vision system to exactly emulate what humans do. For instance, the workers on the narcissi handling conveyor belt are grabbing a handful of flowers with each hand and then instantly estimating that the number of the stems in each hand is 5. A robotic arm with a soft robotic gripper, in tandem with a vision system, could use a similar process. Deep Learning approaches such as that presented for Oncidium Orchids in (Te Tsai, 2019) can for example do both grading by length, and counting of branches, simultaneously. There is also a vibrant research community on soft robot grippers for selective harvesting (Navas et al., 2021), and some of these solutions may be transferable to this application. However, targeted RD&I projects are likely needed to bring such robotic solutions to working prototypes, and ultimately to market.

Task 5: Packing. According to the growers this is quite a substantial part of the process and it takes a lot of effort and manpower. Packing of the flowers involves intricate and delicate handling of flowers and packing materials. As a solution, some of the growers mentioned that they intend to collaborate with third party flower handling companies with large-scale automated conveyors for the purpose. This could help reduce the need for staff considerably.

Task 6: Growth monitoring. This task is common for all growers, and here we frame it generally to combine: disease and pest control, watering, feeding, studying and controlling environmental factors. The growers did not highlight this task as a particular challenge, mostly because of the scale of the operations being quite small. Feeding requires quite a high level of precision, to make sure the chemicals go directly under the plant stem, so it was done manually. As for disease and pest control, it was mostly performed through visual inspection. However, the growers did use automation with regard to weather and soil monitoring outside for data collection. They also used some automatic systems in the protected environment: temperature control, automatically opening and closing the glasshouse windows, automatic watering and heating systems, and automated lighting. There are some potential low hanging fruits with regards to using technology for data collection and environmental control, and some of the growers expressed interest in such solutions. We have seen one of the promising examples for increasing automation for the species grown in containers, where the highly controlled nature of the environment allows for closing the loop on the watering needs with networked soil sensors. Due to the unpredictable terrain and conditions of the open growing environment, robots capable of growth monitoring are still in the research and development stage. UAVs, on the other hand, are accessible and widely used, but may not be economically feasible for the small size of the fields.

Figure 14. The weather station used by one of the growers to monitor outdoor growing conditions.

Other observations. A general challenge with working with flowers comes from the fragility of the stems: for example narcissi stems are soft and hollow. Therefore, any automated handling needs to be precise and gentle.

Another challenge for all the growers we visited was the prohibitive cost of automation. Narrow profit margins in much of the industry make it financially infeasible for the growers to invest in automated solutions. The growers are often also of a scale that make standard automation processes less suitable. In principle, the process of automation is similar to that which exists for the higher-value rose growing sector (e.g. grading and bunching machines). The larger growers we interviewed were aware of such systems, but were unable to justify the investment - the difference in value between the narcissi and rose industry alone was identified by Scented Narcissi as being a ratio of almost 1:50 per stem. The authors did not find any near-market solutions in the literature.

Finally, there were some concerns among remote growers in particular about the dependence on getting an engineer to their difficult-to-reach sites, if and when something breaks in the automation/robotic systems.

Findings for plug plant growers

Eight distinct tasks were identified as pertinent to growing ornamental plug plants from cuttings. These are listed and discussed below:

- Taking cuttings / pinching
- Tray preparation
- Transplanting cuttings
- Weaning
- Trimming
- Pricking out
- Disease/pest control
- Grading

Task 1: Taking cuttings / pinching. Cuttings are taken from mother stock by skilled workers, using handheld cutters to remove the tips of the plants between nodes. The specific technique varies depending on the plant variety. Sometimes the tips of the plants are pinched off instead, to encourage further growth.

It may be challenging to automate this task, as it requires precise and gentle dexterous manipulation - a simple task for human workers, but currently quite challenging for robotic technology. It would be necessary to identify stem orientations and growth patterns, as well as apices and stem distances. See Figure 15 for typical cuts.

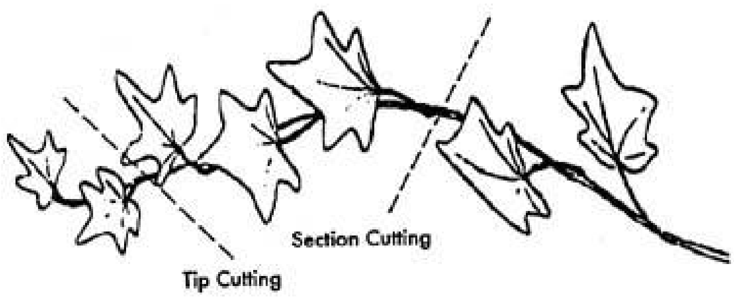


Figure 15. Stem and section cuttings (Texas A&M[2], USA).

There is some work on for example automated pruning of vines (Botterill et al, 2017), but each crop requires a high degree of specialisation in hardware and software. Some learnings can perhaps also be made from selective harvesting robots with cutting tools, for example for

[2] https://aggie-horticulture.tamu.edu/ornamental/a-reference-guide-to-plant-care-handling-and-merchandising/propagating-foliage-flowering-plants/

cauliflower (Klein, et al., 2019) or strawberries (see the pre-commercial Agrobot e-series platform[3]). That is, the “detect, cut then place” operation needed here is not completely dissimilar to that performed by a selective harvesting robot.

Furthermore, the large variety of plant stock poses an additional challenge, as a robotic solution would need a vision system to identify the plant variety, and where to take the cuttings from. This system would need to understand the structure of plants (i.e what is a stem, what is a leaf), and identify these features either through 2D imagery or 3D scans, then be trained to work with different varieties.

Task 2: Tray preparation. The task of filling plug plant trays with soil is usually handled via mechanical automation. For example, Kernock Park Plants have machines that fill plastic trays with plant plugs (soil wrapped in paper), and dib a hole in the centre of each plug ready for a cutting to be inserted. The machines also water the plugs and add nutrients. Kernock Park Plants use two machines - each configured for trays with different arrangements of holes (offset vs aligned). Switching to a supplier of trays with different dimensions would be costly, as the machines are not easily reconfigured. A similar system is used at Fentongollan Farm, but for growing plug plants from seed instead of cuttings (see Figure 16).

b) Seeding machine at Fentongollan Farm - each time it is filled with the seeds that are then pushed into the soil in the trays.

[3] https://www.agrobot.com/e-series

a) Tray preparation machine at Kernock Park Plants.

Figure 16. Machinery for preparing plug plant trays, either for transplanting cuttings, or growing plants from seed.

Task 3: Transplanting cuttings. Human workers take the cuttings and insert them into the trays of pre-prepared soil plugs. Automated solutions to this problem already exist for some types of cuttings - for example, ISO and Visser machines that use computer vision to locate cuttings on a conveyor, then pick-and-place the cuttings with a robotic manipulator. Some of these machines can also be used for transplanting rooted plants, as described below. However, while these machines are cost-effective compared with manual labour (Adegbola, Fisher & Hodges, 2019), they may be prohibitively expensive for small businesses with low hours of operation and high plant diversity. The stems of the cuttings also need to be of a certain length (typically at least 2-5 mm of stem), or the system cannot reliably identify the orientation of the cutting.

a) Workers transplanting cuttings into seedling trays one-by-one.

b) Although this activity can be automated, the production remains mostly manual.

Figure 17: Production line for manually transplanting cuttings at Kernock Park Plants.

Task 4: Weaning. Weaning can be described as the hardening of plants to cold environments. At Kernock Park Plants, this was achieved by moving trays of plug plants between progressively cooler indoor growing areas, as seen in Figure 18. The high variability of cultivars requires different conditions and movement strategies.

This process could be automated using robots for tray movement, using systems much like those already in place for warehouse logistics (e.g. Amazon Warehouse). This would be easier to implement in purpose-built facilities with flat ground, however growers' sites may be built on uneven/inclined terrain - relatively easy for human workers to traverse, but difficult for robots unless they are designed with this in mind (which adds to the cost).

An alternative solution may be to adapt parts of the greenhouses with controllers for many parameters, so instead of moving the plants, the conditions on a particular part of the greenhouse could be changed to have the same effect. Retrofitting this kind of automation to existing infrastructure would be a significant investment, so it may be difficult to justify the cost.

Figure 18. Hardening of succulents. Note the narrow distances between rows.

Task 5: Trimming. Trimming is the cutting of a batch of plants on a tray to a certain height, which depends on the plant variety. This task was already automated by simple cutting machinery at Kernock Park Plants, so there is little need for robotic automation in this area.

Task 6: Pricking out. Pricking out (or repotting) is the removal of seedlings (along with their root system) from initial soil, and transplanting them into larger pots to give them more room to grow. This process is delicate and may be difficult to automate as the plants are very fragile at this early stage, and there is significant variability in technique between different cultivars. The plants, when seen from above, also tend to grow into each other. This is also an obstacle for human manipulation, and some tray designs are developed to facilitate this task: the tray has holes underneath to allow for the plants to pop out when placed and pressed over a pin array. This could perhaps be developed/automated further to help any robotic device attempting the task.

Task 7: Disease and pest control. Disease and pest control involves identifying pests (moths, caterpillars, aphids, thrips and others) or fungal and virus infections present on parts of a plant and removing the affected parts, or making a decision to apply a pesticide to control infections/infestations. This requires highly skilled expert knowledge from the grower or an agronomist, as the indicators of pest and disease can be quite subtle and hard to detect.

This process could be automated through gantry-based mobile camera systems, ground-based inspection robots, or low-flying indoor drones.

An inspection and disease control system based on a gantry, a mobile ground robot or an indoor drone is a trade-off between price and robustness, by exchanging a hardware problem for a software and reliability problem. A gantry would be the most robust solution, but would require considerable changes to the production cycle, where the growing plants would need to be presented to the gantry system or a whole growing area would need to be accessible to the gantry. A ground based inspection robot would be the intermediate solution, with few changes needed to be done to the production site - maybe perhaps increased clearance for robot movement. An indoor drone solution would need no change in production site, however it would require a robust solution to unmanned navigation indoors, which currently is a research topic (de Azambuja et al., 2021).

However, the breadth of plant varieties also poses problems here, as they will each suffer from different pests and diseases, and will present different symptoms. This would make it difficult to train an automated system to reliably detect the presence of pests/disease, but a certain number of false positives may be tolerable if such a system proves to be a net benefit.

Task 8: Grading. Grading requires plants to be removed from a tray, evaluated as a set and then graded. From the growers' description, this is an expensive, but necessary system and would ideally be automated, as it is a very tedious task (error prone, difficult to do when more than 3 classes are desired, labourers do not like doing this). It was also mentioned that an "in place" grader - that would look at a tray and place each plant directly in their corresponding tray class - instead of removing them, one by one, scanning all, then placing them, would be best. See Figure 19 for an overview.


a) Succulents grown on trays ready for grading.


b) Another variety showing how often these plants grow into each other with no gaps.

Figure 19. One of the difficulties for automatic grading: the plants sometimes overlap creating confusion for the computer vision segmentation

Automatic grading machines already exist (e.g. [ISO Grade 7000]), however they are not currently designed with such a large diversity of plant varieties in mind. Such machines use computer vision techniques to classify each plant of a particular variety based on its size, then extracts the plug plant and inserts it into the appropriate tray. The picking mechanism used by these machines is often top-down, so will not work well with plug plants that grow beyond the diameter of the soil plug.

Commercial off-the-shelf robot arms are becoming more and more affordable, so may soon offer a cheaper and more flexible solution. A human worker could place trays of plug plants on a mobile trolley fitted with an overhead camera and robot arm for grading - the camera would be used to identify the grade of each plant, which the arm could then pick-and-place into categorised trays. There has been some work on using robots to learn from humans how to perform this type of task (Sena & Howard, 2020). To overcome the problem of plants that grow beyond the diameter of their plugs, simple mechanical automation could be used to push the soil plugs out of the tray from below, so the robot arm can grip them from the side.

The primary challenge for this kind of automation is the image processing required to automatically detect the grade of each plant, particularly across many plant varieties. Traditional machine vision solutions are programmed by hand to detect particular features (e.g. sepal length/width), and would need to be rewritten to work for each plan variety (of which there may be hundreds or thousands). By contrast, modern machine learning approaches can learn the relationship between photographic imagery and the grade of each plant automatically. However, they require significant quantities of training data - images labelled with the correct grade by a human expert, and would need to be trained on each variety individually.

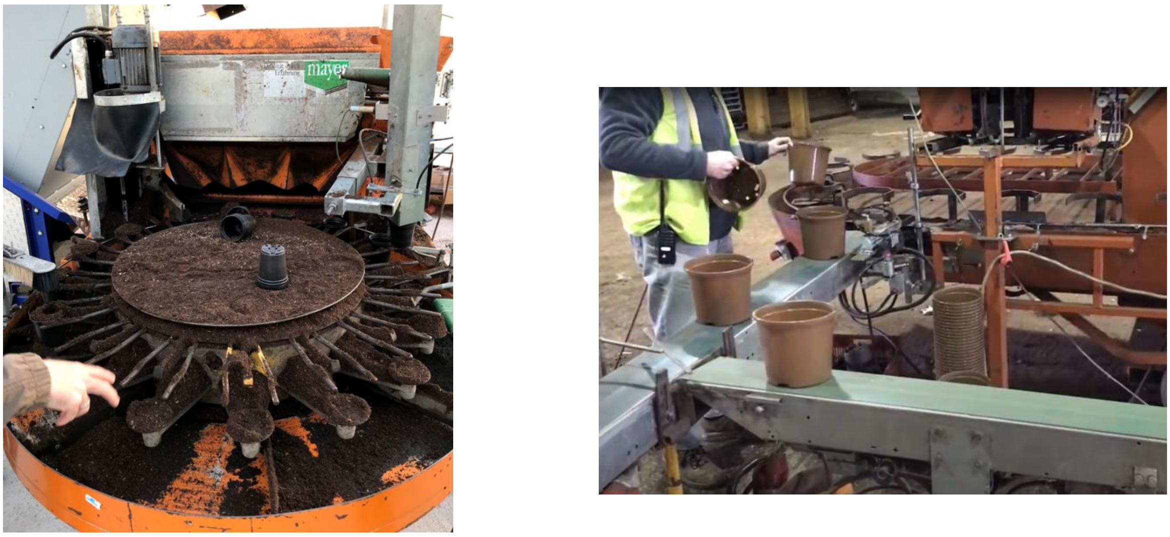
Given that the grading process is already being performed by human workers, these data sets required for machine learning could be collected on-the-job during a transition period. Workers could place a tray of plants under an overhead camera, tell the system the plant variety (e.g. scan tray barcode), then tell the system the grade of each plug plant (e.g. via a touchscreen interface). Once sufficient data has been collected, the system should be able to automatically classify the grade of each plant variety it has been trained on.

Findings for nursery stock

The visits to Darby Nursery Stock and Johnsons of Whixley highlighted some of the challenges these types of nurseries face. The main tasks for these growers included:

- Preparing plant pots (filling with soil dibbing holes).
- Putting young plants into pots to be grown-on.
- Transporting potted plants between indoor and outdoor growing environments
- Placing potted plants in growing areas, and reorganising them after gaps are created due to sale of a selected grade
- Irrigation (already automated)
- Inspection for pests/disease - by grower or agronomist
- Labelling potted plants for sale (e.g. growing instructions card, barcode)
- Configuring trolley shelf heights, to accommodate plants for a particular order
- Transferring potted plants to trolleys, for sale to garden centres
- Transport of trolleys

Most of these tasks are common with the other types of growers, and so will not be discussed further here. However, it is worth noting that plant pots are usually filled with soil via mechanical automation. See Figure 20 for examples.



b)

a)

Figure 20. Pot filling machine at a) Kernock Park Plants, and b) Darby Nursery Stock.

Finally, Figure 21a shows the trolley used for sale. The trolley is configured for plants of varying heights, i.e. the best configuration is determined by human workers for each order. The reconfiguration and loading of these trolleys could be automated through the use of a robot arm, and optimisation algorithms that determine the best shelf spacing based on the plants to be loaded. Such a solution would be of use to multiple growers, as the trolleys follow a standard design across the sector. The movement of the trolleys could also be automated, using wheeled robots to push or tow them while avoiding human workers.

Figure 21b shows the large variety of pot plants grown in controlled conditions, with automated irrigation. As mentioned previously, the organisation and reorganisation of potted plants could be automated using small mobile ground-based robots that can pick up and place pots of varying sizes. See Figure 13 for examples. This would significantly reduce the day-to-day manual labour required, and lower physical demands on the workers (less bending over). In principle there are no prohibitive technical barriers for using the robots for this task. The main constraints are whether the cost of acquiring or renting the robots is justified for the scale of operations of each nursery, and what modifications are needed to enable the robots to work effectively. Cost is also the main driver for nurseries in other geographies. A recent survey of 48 nurseries and greenhouses in the US and Canada found that for nurseries the biggest barrier for investing in automation was cost (at 50%), while 30% listed the lack of options on the market, and 20% listed the current nursery layouts as being unfavourable for automation (Josefsson, 2019). When there is a lack of options on the market, custom solutions may also be possible, but developing a customised robot for a particular application may be difficult to justify given that the possible market could be quite small. This could potentially be addressed by closer collaboration between academia, growers, and industry partners through grants schemes for interdisciplinary projects.

a) Trolley of plants ready for sale.

b) View of greenhouse.

Figure 21: Details from Darby Nursery Stock.

Finally, there may be opportunities to use robotics for plant inspection to detect early signs of pest/disease before it spreads. This inspection is currently done by the growers themselves, or hired agronomists, and the sheer scale of these sites is difficult to cover on foot by a limited number of domain experts. If early signs are missed, then outbreaks may occur, which are costly to the business. Autonomous ground-based robots or low-flying drones could be used to image the plants on a regular basis, and either identify signs of pests/disease themselves, or flag areas of suspicion for human experts to inspect.

General discussion

The main project objectives were to identify and explore issues limiting uptake of automation and robotics for ornamentals by the horticultural industry, and to identify potential solutions to these issues.

We have identified several different possible applications of automation and robotics, sometimes in combination with machine learning with varying degrees of complexity. Some of the work likely to influence solutions in this sector comes from state-of-the-art agricultural robotics, and related algorithms (Duckett, et al. 2018). Problems range from ones that have decent solutions, such as ISO/Visser cutting machines and warehouse movement, to more complex applications that would require more change in production facilities. For example chaining of activities, handling of very delicate plant material with robots, movement in narrow spaces, and multi-arm operations.

The automated transplanter is now widely used, also in the UK[4]. There are also good examples of a more expansive approach to automation in large operations, where all of the steps can be integrated into a large conveyor belt machine with different stages[5]. For smaller scale operations, or where there is a very large range of plants to handle, a more flexible robotic approach may be taken, like that used in the current automated solutions for picking fruits/berries. That is, where autonomous robotic systems are able to operate in complex environments by relying on extensive 3D and colour vision data.

Current existing agricultural robotic research (Duckett et al., 2018), and near-commercial solutions for picking fruits/berries, such as those of Saga Robotics (Ås, Norway), Dogtooth Technologies (Cambridge, UK), Fieldwork Robotics (Cambridge, UK), and Octinion (Leuven, Belgium), do not directly fit the requirements necessary for robust automation of activities in ornamental nurseries. However, the level of complexity is, in our understanding, similar to some of the problems being solved for these systems. We believe further research is necessary to determine how well changes would matter-of-factly translate into this domain. Light and human-friendly robot arms can also be trained for new tasks by human operators (Sena & Howard, 2020).

There are relevant advanced providers of robotic solutions for the nursery and agriculture industries, at or near-market. For example Advanced Intelligent Systems (Burnaby, Canada), with its BigTop autonomous robot. This robot is used for pot moving, placing and spacing in greenhouse nurseries[6]. Another type of existing automation that would be relevant to ornamentals is warehouse automation, which is seeing increased uptake also from smaller companies, and which can be applied in refrigerated spaces[7].

While there were less obvious opportunities for further automation for the orchid production at Double H Nurseries, the grading process stood out as a possibility. That is, supplementing or replacing human experts with advanced vision and machine learning systems. This was

4 https://www.rotomation.co.uk/transplanters
5 https://ahdb.org.uk/news/automation-and-robotics-in-6-dutch-horticultural-nurseries
6 https://www.ai-systems.ca/bigtop-autonomous-mobile-robot/
7 https://www.mmh.com/wp_content/viastore_wp_15_myths_warehouse_automation_020916.pdf

also seen as an opportunity for several of the other growers, as a first step towards automating their business.

There is a large body of work in the literature on applying Computer Vision and Machine Learning to agricultural crops (Kamilaris, & Prenafeta-Boldú, 2018; Kamilaris, Kartakoullis, & Prenafeta-Boldú, 2017), which may be relevant also here. The training data for these algorithms could be obtained through a transitionary period in which human experts complete grading tasks on-site, assigning a grade to the images/scans obtained of each plant as they pass through the production line. This data could be collected with little additional effort, using simple input systems such as touch-screen interfaces during the normal grading process to record the grade of each plant. Once sufficient data has been obtained to train a machine learning algorithm, the grading process could then be automated by predicting the grade of previously unseen plants based on features observed in imagery of plants from the training data. General-purpose plant imaging booths could be designed for conveyor systems such as those at Double H Nursery, but fine-tuning of the machine learning algorithm would require consultancy to create a bespoke solution for reliable grading. Grading accuracy is most likely dependant on crop variety and type, but encouraging results from Zhou et al., 2020, show classification accuracy in grading of broccoli heads close to 90%; de Luna, 2020, show a grading classification accuracy in tomato crops of upwards of 95% and Tian et al, 2017 show a classification accuracy in grading seedlings of 98%. Such systems only require a photography rig, which can be simplified with modern algorithms, to inspect a single isolated plant and either an internet connection[8] or an adequately powered computer[9], with around 100 to 1000 images required per class (Cireşan et al., 2012; Dernoncourt et al., 2016; Shahinfar et al., 2020).

The project also aimed to include feedback from growers about what they perceive to be the best use for a robotic arm or other robotic solutions on their sites. Feedback was received during phone interviews and visits, as outlined above, and used to shape this report and the overall discussion on the topic. We also developed a survey during the project which aimed to collect information that would help us to understand broader limitations of robotics for ornamental horticulture. Unfortunately, the survey was ultimately not distributed to the growers, but it is included for reference in Appendix A.

[8] A perhaps more robust approach would be to deploy classification and grading as a software as service, to guarantee that classification is always done using the most up-to-date algorithm and that learning is shared, that is, we avoid needing to train locally the grading system for newer varieties.

[9] Note that several of the tested algorithms were classic computer vision Machine Learning algorithms, such as K-Means and Support Vector Machines and do not require any special hardware to be executed. Those rely more on photos that have always the same appearance, that is, taken from a proper rig with controlled illumination with plants that are of the same kind as the dataset in which those algorithms were trained.

Conclusions

The main conclusion of the project is aligned with previous work in the area, in that there are significant challenges in applying automation and robotic solutions for dealing with the large variability in plant species and varieties in ornamentals, but that there is a range of grower-specific and plant-specific opportunities that should be followed up. Most robotic solutions will normally apply to single plant species, i.e. plant types with defined morphological characteristics that the robot can be programmed and fine-tuned for. Taking that robotic system and applying it to another plant species with a different morphology and requirements would mean: (i.) in the best case scenario, re-programming and obtaining new datasets for the machine learning algorithms, (ii.) in the worst case, making hardware modifications to the robot as well. In nursery stock where there are 100s or 1000s of species and varieties then "one-size" will not fit all. Simpler automated solutions, like conveyor belt systems, also require large scales of operation to make the investment worthwhile.

However, within each of the three categories of growers covered in this report; i.e. cut-stem flower growers, plug plant growers, and nursery stock, there are specific challenges that can likely be met by increased automation in the near to medium term. This includes, but is not limited to: (i). automated counting and grading of specific cut stem flowers with a lower price-point, (ii). automated grading of a (limited) range of different plug plants, (iii). cost effective mobile robots for addressing gapping in UK nursery plant stock, (iv). flexible robotic handling of potted plants by light industrial robot arms taught by human workers.

In addition, there are commonalities to the challenges across growers that may be exploited. For example in grading, a tedious and error-prone job, and where automated systems can perhaps make a difference in the short to medium term. However, this still requires some of the issues related to enabling such systems to handle a wide enough array of crops to be resolved. Targeted RD&I is needed to explore these opportunities, and to ensure the solutions proposed are grounded in the needs of the growers, both practically and financially.

Knowledge and Technology Transfer

The principal knowledge transfer activity for this project:

- Discussions with growers on automation and robotics during 8 visits.
- This report, which outlines challenges and possibilities related to automation.
- The survey in Appendix A.

References

Adegbola, Y. U., Fisher, P. R., & Hodges, A. W. (2019). Economic evaluation of transplant robots for plant cuttings. Scientia Horticulturae, 246, 237-243.

Azambuja, Ricardo de, Hassan Fouad, and Giovanni Beltrame. 'When Being Soft Makes You Tough: A Collision Resilient Quadcopter Inspired by Arthropod Exoskeletons'. *ArXiv:2103.04423 [Cs]*, 7 March 2021. http://arxiv.org/abs/2103.04423.

Bac, C. W., van Henten, E. J., Hemming, J., & Edan, Y. (2014). Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *Journal of Field Robotics*, *31*(6), 888-911.

Botterill, T., Paulin, S., Green, R., Williams, S., Lin, J., Saxton, V., Mills, S., Chen, X. and Corbett-Davies, S., 2017. A robot system for pruning grape vines. Journal of Field Robotics, 34(6), pp.1100-1122.

Cireşan, Dan C., Ueli Meier, and Jürgen Schmidhuber. 'Transfer Learning for Latin and Chinese Characters with Deep Neural Networks'. In *The 2012 International Joint Conference on Neural Networks (IJCNN)*, 1–6, 2012. https://doi.org/10.1109/IJCNN.2012.6252544.

Comba, L., Gay, P., & Aimonino, D. R. (2012). Robotic solutions for pot-plant nurseries. In *Information Technology, Automation and Precision Farming. International Conference of Agricultural Engineering-CIGR-AgEng 2012: Agriculture and Engineering for a Healthier Life, Valencia, Spain, 8-12 July 2012*. CIGR-EurAgEng.

Dernoncourt, Franck, Ji Young Lee, Ozlem Uzuner, and Peter Szolovits. 'De-Identification of Patient Notes with Recurrent Neural Networks'. *ArXiv:1606.03475 [Cs, Stat]*, 10 June 2016. http://arxiv.org/abs/1606.03475.

Duckett, T., Pearson, S., Blackmore, S., Grieve, B., Chen, W. H., Cielniak, G., ... & Yang, G. Z. (2018). Agricultural robotics: the future of robotic agriculture. *arXiv preprint arXiv:1806.06762*.

Hemming, J., Pekkeriet, E. and Van Der Schoor, R., (2010) AUTOMATIC GRADING OF ANTHURIUM CUT FLOWERS USING 3D COMPUTER VISION. CSBE100934 – Presented at 8th World Congress on Computers in Agriculture (WCCA) Symposium, Québec City, Canada June 13-17, 2010.

Josefsson, S. (2019). Adoption of Automation in the Horticulture Industry: A Case Study at a Robotics Company in the US and Canada. Master Thesis TRITA-ITM-EX 2019:208, KTH Industrial Engineering and Management, Sweden.

Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). A review on the practice of big data analysis in agriculture. *Computers and Electronics in Agriculture*, *143*, 23-37.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, *147*, 70-90.

Klein, F.B., Wilmot, A., de Tejada, V.F., Rodriguez, B.L., Requena, I., Busch, S., Rondepierre, A., Auzeeri, T., Sauerwald, T., Andrews, W.F.P. and Rihan, H. (2019). Proof-of-concept modular robot platform for cauliflower harvesting. In Precision agriculture'19 (pp. 244-255). Wageningen Academic Publishers.

Luna, Robert de, Elmer Dadios, Argel Bandala, and Ryan Vicerra. 'Tomato Growth Stage Monitoring for Smart Farm Using Deep Transfer Learning with Machine Learning-Based Maturity Grading'. *AGRIVITA Journal of Agricultural Science* 42 (1 February 2020). https://doi.org/10.17503/agrivita.v42i1.2499.

Mohamed, A., Shaw-Sutton, J., Green, B.M., Andrews, W., Rolley-Parnell, E.J., Zhou, Y., Zhou, P., Mao, X., Fuller, M.P. & Stoelen, M.F. (2019). Soft manipulator robot for selective tomato harvesting. In Precision agriculture'19 (pp. 244-255). Wageningen Academic Publishers.

Navas, E., Fernández, R., Sepúlveda, D., Armada, M., & Gonzalez-de-Santos, P. (2021). Soft Grippers for Automatic Crop Harvesting: A Review. *Sensors*, *21*(8), 2689.

Sena, A., & Howard, M. (2020). Quantifying teaching behavior in robot learning from demonstration. *The International Journal of Robotics Research*, *39*(1), 54-72.

Sena, A. (2019). GROWBOT: A Grower-Reprogrammable Ornamental Plant Production Tasks, AHDB Report. https://ahdb.org.uk/hns-po-194-growbot-a-grower-reprogrammable-robot-for-ornamental-plant-production-tasks-phd-studentship

Shahinfar, Saleh, Paul Meek, and Greg Falzon. 'How Many Images Do I Need? Understanding How Sample Size per Class Affects Deep Learning Model Performance Metrics for Balanced Designs in Autonomous Wildlife Monitoring'. *ArXiv:2010.08186 [Cs, Stat]*, 16 October 2020. http://arxiv.org/abs/2010.08186.

Te Tsai, Y., Wu, H. C., & Zhu, S. M. (2019, September). A simple algorithm for oncidium orchid cut flower grading with deep learning. In *International Symposium on Pervasive Systems, Algorithms and Networks* (pp. 283-288). Springer, Cham.

Tian, Subo, Zifan Wang, Jifeng Yang, Zichen Huang, Ruili Wang, Liping Wang, and Jianghui Dong. 'Development of an Automatic Visual Grading System for Grafting Seedlings'. *Advances in Mechanical Engineering* 9, no. 1 (1 January 2017): 1687814016686265. https://doi.org/10.1177/1687814016686265.

Yulianto, D., & Raibhu, S. (2018). Design of Semi-automatic Plant Media Bagging Machine for Container Plant Nursery. Journal of Advanced Agricultural Technologies Vol, 5(1).

Zhou, Chengquan, Jun Hu, Zhifu Xu, Yue Jibo, Hongbao Ye, and Yang Guijun. 'A Monitoring System for the Segmentation and Grading of Broccoli Head Based on Deep Learning and Neural Networks'. *Frontiers in Plant Science* 11 (15 April 2020). https://doi.org/10.3389/fpls.2020.00402.

Appendix A - Survey on robot usage, limitations, and potential

(Available online at:

https://plymouth.onlinesurveys.ac.uk/ahdb-ornamental-robotics-survey)

1. *Please choose your primary business sector:*
    a. Bulbs and Outdoor Flowers
    b. Hardy Nursery Stock
    c. Protected Ornamentals
    d. Other (please specify)
2. *Please choose your secondary business sector:*
    a. Bulbs and Outdoor Flowers
    b. Hardy Nursery Stock
    c. Protected Ornamentals
    d. N/a
    e. Other (please specify)
3. *How many varieties do you work with?:*
    a. ---
4. *Please list your three main varieties:*
    a. ---
    b. ---
    c. ---
5. *What size is your business?*
    a. 0-2 ha
    b. 2-5 ha
    c. 6-10 ha
    d. 11-20 ha
    e. 21-50 ha
    f. 51-100 ha
    g. 101-200 ha
    h. 201-500 ha
    i. >500 ha
6. *What is the peak number of people you employ during the typical growing season?*
    a. 0-5 ppl
    b. 6-10 ppl
    c. 11-100 ppl
    d. >100 ppl
7. *What tasks are relevant to your operations?*

a. Seeding
b. Field preparation
c. Compost treatment
d. Spawning
e. Casing
f. Tray/block/pot transport
g. Translaning/planting
h. Watering
i. Fertilising
j. Application of biological controls
k. Application of chemical controls
l. Monitoring
m. Harvesting
n. Grading
o. Bunching
p. Packing
q. On-site transport
r. Stacking
s. Storage
t. Wrapping
u. Product transport
v. Other: ---

8. *What tasks in your system are currently automated (replace human labour with mechanical operations)?*
    a. Seeding
    b. Field preparation
    c. Compost treatment
    d. Spawning
    e. Casing
    f. Tray/block/pot transport
    g. Translaning/planting
    h. Watering
    i. Fertilising
    j. Application of biological controls
    k. Application of chemical controls
    l. Monitoring
    m. Harvesting

n. Grading
o. Bunching
p. Packing
q. On-site transport
r. Stacking
s. Storage
t. Wrapping
u. Product transport
v. Other: ---

9. *What tasks in your system currently involve robotics (an automated task which includes feedback and sensing)?*
    a. Seeding
    b. Field preparation
    c. Compost treatment
    d. Spawning
    e. Casing
    f. Tray/block/pot transport
    g. Translaning/planting
    h. Watering
    i. Fertilising
    j. Application of biological controls
    k. Application of chemical controls
    l. Monitoring
    m. Harvesting
    n. Grading
    o. Bunching
    p. Packing
    q. On-site transport
    r. Stacking
    s. Storage
    t. Wrapping
    u. Product transport
    v. Other: ---
10. *Where would you most like to see developments in either automation or robotics?*
    a. Seeding
    b. Field preparation
    c. Compost treatment

d. Spawning
e. Casing
f. Tray/block/pot transport
g. Translaning/planting
h. Watering
i. Fertilising
j. Application of biological controls
k. Application of chemical controls
l. Monitoring
m. Harvesting
n. Grading
o. Bunching
p. Packing
q. On-site transport
r. Stacking
s. Storage
t. Wrapping
u. Product transport
v. Other ---

11. *Could you explain the details of the processes you would like to see automated (mechanically or robotically)?*
    a. ---
12. *What do you see as the main obstacles for the automation of those processes?*
    a. ---
13. *What is the most important piece of new technology you would like to see?*
    a. ---
14. *Are you currently developing in-house automation/robotics solutions?*
    a. Yes, if yes, which? ---
    b. No
15. *Are you planning on investing in automation or robotics in the next:*
    a. 0-1 year
    b. 2-3 years
    c. 3-5 years
    d. 5-10 years
    e. >10 years
    f. No
        - *If so, how much do you envisage spending?*

- 0-1% of turnover
- 2-5% of turnover
- 6-10% of turnover
- 11-20% of turnover
- >21% of turnover

- *Could you give an estimate of your company's turnover?*

16. *Are you involved in automation/robotics research projects?*
    a. *Yes*
    b. *No*
        - *If possible, could you specify: ---*
17. *Would to see more research into automation/robotics at a Government level?*
    a. Yes
    b. No
18. *How can AHDB best support the future automation/robotics aspirations of your business?*
    a. Leave investment to commercial arena
    b. Pre commercial research
    c. Case study/updates of new developments
    d. Study tours focusing on new technologies
    e. Any other ways? : --
19. *In the context of all AHDB Horticulture research needs, how important is this topic to you?*
    a. 1 - Not important
    b. 2 - A little important
    c. 3 - Quite important
    d. 4 - Important
    e. 5 - Very important
20. *Have you actively searched for information on automation/robotics?*
    a. Yes
    b. No
        - *If so, where do you get information on automation/robotics?*
            - Advisors
            - Growers
            - Service providers
            - Press
            - Internet
            - Research papers

- Research events
- UK trade shows
- Overseas trade shows
- Other: ---

21. *Would you like AHDB Horticulture to provide more information on automation/robotics?*
    a. Yes
    b. No
    - *If so, in what format?*
        - Events
        - Web content
        - Webinars
        - Publications
        - Dedicated KE package (like GrowSave)
22. *Any other comments on the topic?*
    a. --
23. *If you are happy to be contacted on this topic please add your email address:*
    a. --

