Implementation and applications of harvest fleet route planning

Industrial Ph.D. dissertation by

Andrés Villa-Henriksen

Aarhus University Dept. of Electrical and Computer Engineering
& Agro Intelligence ApS

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Abstract

In order to support the growing global population, it is necessary to increase food production efficiency and at the same time reduce its negative environmental impacts. This can be achieved by integrating diverse strategies from different scientific disciplines. As agriculture is becoming more data-driven by the use of technologies such as the Internet of Things, the efficiency in agricultural operations can be optimised in a sustainable manner. Some field operations, such as harvesting, are more complex and have higher potential for improvement than others, as they involve multiple and diverse vehicles with capacity constraints that require coordination. This can be achieved by optimised route planning, which is a combinatorial optimisation problem. Several studies have proposed different approaches to solve the problem. However, these studies have mainly a theoretical computer science perspective and lack the system perspective that covers the practical implementation and applications of optimised route planning in all field operations, being harvesting an important example to focus on. This requires an interdisciplinary approach, which is the aim of this Ph.D. project.

The research of this Ph.D. study examined how Internet of Things technologies are applied in arable farming in general, and in particular in optimised route planning. The technology perspective of the reviewing process provided the necessary knowledge to address the physical implementation of a harvest fleet route planning tool that aims to minimise the total harvest time. From the environmental point of view, the risk of soil compaction resulting from vehicle traffic during harvest operations was assessed by comparing recorded vehicle data with the optimised solution of the harvest fleet route planning system. The results showed a reduction in traffic, which demonstrates that these optimisation tools can be part of the soil compaction mitigation strategy of a farm. And from the economic perspective, the optimised route planner of an autonomous field robot was employed to evaluate the economic consequences of altering the route in selective harvesting. The results presented different scenarios where selective harvest was not economically profitable. The results also identified some cases where selective harvest has the potential to become profitable depending on grain price differences and operational costs. In conclusion, these different perspectives to harvest fleet route planning showed the necessity of assessing future implementation and potential applications through interdisciplinarity.

Sammenfatning

For at støtte klodens voksende befolkning er det nødvendigt at øge fødevareproduktions effektivitet og samtidig formindske dens negative miljøindvirkninger. Dette kan opnås ved at integrere diverse strategier fra forskellige videnskabelige discipliner. Da landbrug bliver mere data drevet takket være brugen af teknologier såsom 'Internet of Things', kan effektiviteten af landbrugsoperationer blive optimeret på en bæredygtig måde. Nogle markoperationer, f.eks. høst, er mere komplekse og har større forbedringspotentiale end andre, fordi de involverer flere forskellige maskiner med kapacitetsbegrænsninger, som kræver koordinering. Dette kan opnås ved at bruge optimeret ruteplanlægning, som er et problem i kombinatorisk optimering. Adskillige studier har forslået forskellige fremgangsmåder for at løse problemet. Alligevel har disse studier hovedsageligt et teoretisk datalogisk perspektiv og mangler systemets perspektiv, som dækker implementering og anvendelserne af optimeret ruteplanlægning i alle markoperationer, hvori høst afgør et vigtigt eksempel at sætte fokus på. Dette kræver en tværfaglig fremgangsmåde, som er målet af dette Ph.d.-projekt.

Forskningen i dette Ph.d.-studie undersøgte hvordan 'Internet of Things' teknologier er anvendt i markbrug generelt, og i særdeleshed i optimeret ruteplanlægning. Teknologiens perspektiv i gennemgangsprocessen skaffede den nødvendige viden til at adressere den fysiske implementering af et høst maskinflåde ruteplanlægningssystem, som sigter mod at minimere samlet høsttid. Fra et miljømæssigt synspunkt blev jordpakningsrisici fra tung trafik i marken under høst vurderet ved at sammenligne optaget maskindata med den optimerede løsning fra høst maskinflåde ruteplanlægningssystemet. Resultaterne viste en reduktion af trafik, som beviser at disse optimerede ruteplanlægningsværktøjer kan være en del af gårdens jordpakningsforebyggende strategier. Og fra det økonomiske perspektiv, blev en optimeret ruteplanlægger fra en selvkørende markrobot brugt for at vurdere de økonomiske konsekvenser af ruteændringer i selektiv høst. Resultaterne fremlagde forskellige scenarier hvor selektiv høst ikke var økonomisk gavnlig. Resultaterne viste også nogle tilfælde hvor selektiv høst har potentiale for at blive økonomisk gavnlig, afhængig af korn prisforskel og driftsomkostninger. Som konklusion, viste disse forskellige perspektiver af høst maskinflåde ruteplanlægning nødvendigheden af at vurdere fremtidig implementering og potentielle applikationer ved hjælp af tværfaglighed.

Preface

This Ph.D. dissertation is the outcome of the collaboration between industry and academia as part of the Industrial Ph.D. programme at Aarhus University, Department of Electrical and Computer Engineering - Communication, Control and Automation. The project was partly funded by the Innovation Fund Denmark within the project Future Cropping – Intelligent Harvest; by the European Union's Horizon 2020 research and innovation programme under grant agreement no. 731884, Internet of Food and Farm (IoF2020) – Farm Machine Interoperability, and by the research and innovation programme under grant agreement no. 818182, SmartAgriHubs – Valued Grain Chain.

The Ph.D. dissertation is structured as a collection of manuscripts organised into chapters following an interdisciplinary approach to optimised route planning in harvest operations. These manuscripts resulted in scientific papers in diverse scientific journals and conference proceedings. An overview of the publications can be found at the end of the introduction. The dissertation starts with a review of the state-of-the-art of optimised route planning in general and in harvest operations in particular. From the reviewing process some research gaps were identified. These define the objectives of the Ph.D. project. Within the interdisciplinary approach, chapter 2 and 3 address the technological perspective of the Internet of Things and its integration and implementation on harvest fleet route planning systems. Chapter 4 assesses the environmental influence of optimised route planning in harvest operations on the risk of soil compaction. Chapter 5 focuses on the economic aspects of route planning in different selective harvesting scenarios. And chapters 6 and 7 discuss, put in perspective and draw conclusions on the work done during the Ph.D. programme.

Andrés Villa-Henriksen, July 2021

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I am very grateful for the different national and international projects I have been part of during this period, which have partially funded my research. They have enhanced my knowledge from different industrial and scientific perspectives. And they have also increased my network for future exciting collaborations.

I would like to thank my colleagues within the Department of Engineering who have helped me along the way with the scientific insight and experience. Likewise, I am grateful for the help provided by the co-authors in the published work in my Ph.D.

On the personal side, I want to thank my wife and 3 kids who supported me in many ways showing great understanding and patience during this time.

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Chapter 1 Introduction

The global human population growth along with increasing consumption levels per-person, are degrading the environment worldwide, depleting its natural resources, as well as challenging the global food supply (Godfray *et al.*, 2010; Tilman *et al.*, 2011; Crist, Mora and Engelman, 2017). Furthermore, these challenges are exacerbated by climate change, which makes food production unforeseeable and as a consequence less reliable. Increasing the efficiency in food production systems while reducing the negative environmental impacts associated with agriculture can be achieved by multifaceted strategies from different fields of study. One of these strategies is data-driven agriculture (Tilman *et al.*, 2002; Sørensen *et al.*, 2010; Day, 2011; Foley *et al.*, 2011; Wolfert *et al.*, 2017), which by the appropriate use of its technologies can improve the efficiency in agriculture from different fronts. Improving the efficiency in agricultural operations targets also the economic aspect, which is essential for its adoption among modern agricultural producers (Pierpaoli *et al.*, 2013). One of the data-driven agricultural strategies to improve the efficiency in agricultural operations is optimised route planning and its application in harvest operations (Bochtis, Sørensen and Busato, 2014).

In the same manner there are many sides to why there is increased demand in food supply, there are also many different solutions that cannot solve the problem isolated. Furthermore, as agriculture is an interdisciplinary field, these solutions need to be addressed from an interdisciplinary approach too. Improving the efficiency of agricultural operations by optimised route planning cannot be only covered by the theoretical computer science point of view, but should be connected with perspectives from across different disciplinary boundaries. Starting from the combinatorial optimisation problem, its implementation and application in harvesting operations needs to be addressed from different disciplines, so that the apparent contradictory goals of improving agricultural efficiency and reducing environmental impact can be creatively covered.

1.1 Background

There is potentially high efficiency gains in the coordination and route optimisation of a fleet of agricultural vehicles in collaborative operations such as harvesting (Moysiadis *et al.*, 2020; Nilsson and Zhou, 2020). The aim for efficiency is also encouraged by the reduced workability timeframes farm managers have to complete different operations (Edwards *et al.*, 2015a; Seyyedhasani and Dvorak, 2017). Besides increasing operational efficiency, route planning in harvest operations can have other concrete goals in the optimisation, *e.g.* reducing the risk for soil compaction (Bochtis, Sørensen and Green, 2012). Harvest operations involve multiple heterogeneous machines with capacity constraints that need to collaborate in a field in a coordinated manner. Optimising the route planning in these operations is not without challenges and is essential for the employment of robotics and autonomous agricultural vehicles (Kayacan *et al.*, 2015; Bechar and Vigneault, 2016; Ren and Martynenko, 2018; Moysiadis *et al.*, 2020; Villa-Henriksen, Edwards, *et al.*, 2020; Araújo *et al.*, 2021). Nonetheless, several studies have proposed specific solutions that are covered in this chapter and conform the background for the research presented in this Ph.D. dissertation.

1.1.1 Vehicle routing problem in agricultural operations

The VRP and its variations have provided optimised planning solutions for vehicle fleets in many diverse applications, *e.g.* transportation logistics, public transport or sales routing (Golden, Assad and Wasil, 2002). VRP, a generalised version of the classic travelling salesman problem (TSP), aims to find the optimal route or set of routes to be followed by a fleet of vehicles in order to visit a set of spatially dispersed points. This challenging combinatorial optimisation problem was firstly described in a real-world application by Dantzig & Ramser (1959). Later, new approaches were presented that instead of aiming for a globally optimal solution, sought for solutions that would approximate to the globally optimal in a reduced amount of time, *e.g.* by a greedy heuristic algorithm (Clarke and Wright, 1964). Depending on the constraints that can be added to the VRP, *e.g.* route length, time windows or capacity constraints, different variants have been described. These respond to the necessities of the different applications of VRP in practice. The approaches to solve these variants are also very diverse ranging from exact methods, such as branch-and-bound and branch-and-cut algorithms; to classical heuristic methods; and more recently meta-heuristic methods, such as Simulated and Deterministic Annealing, Tabu Search, Genetic Algorithms, Ant Systems, or Neural Networks (Toth and Vigo, 2002). The metaheuristic methods are of special interest as they are applicable to large numbers of problem instances and are more robust, in the sense that they can be more easily extended to account for the diverse constraints found in real-life applications.

Even though all field operations in arable farming involve vehicles, it is relatively recent that VRP has been applied to agricultural field operations (Bochtis and Sørensen, 2009; Oksanen and Visala, 2009). The main challenge of VRP for field operations is that they are an NP-hard problem (Oksanen and Visala, 2009). NP stands for non-deterministic polynomial time and hard characterises that the problem cannot be solved in polynomial time, which in practice means that the optimal solution is unreachable, and require therefore methods that approximate to the globally optimal solution in a reasonable amount of time, *e.g.* meta-heuristic methods (Toth and Vigo, 2002). Additionally, the diversity of field operations requires adapted methods for specifically the type of task to perform in the field. Some more simple operations require a single vehicle to cover the whole field with trafficability constraints, *e.g.* tillage, or mowing, while others more complex need to coordinate a fleet of vehicles with different functions and capacities, *e.g.* grain harvesting. Another aspect to the complexity of applying VRP in agricultural field operations is how the diversity of fields and operations can be represented as a mesh of nodes to be visited, with in-field attributes (rows and headlands), and inter-field configurations (gates, depots and connecting road networks) (Bochtis and Sørensen, 2009, 2010; Jensen *et al.*, 2012; Zhou *et al.*, 2014). Whereas some operations can be simplified by representing each row with two nodes, one on each end, others like harvesting require different representations for the offloading points or the out-of-field depot (Figure 1). Consequently, it is just over a decade that researchers started studying VRP solutions in an arable farming context.

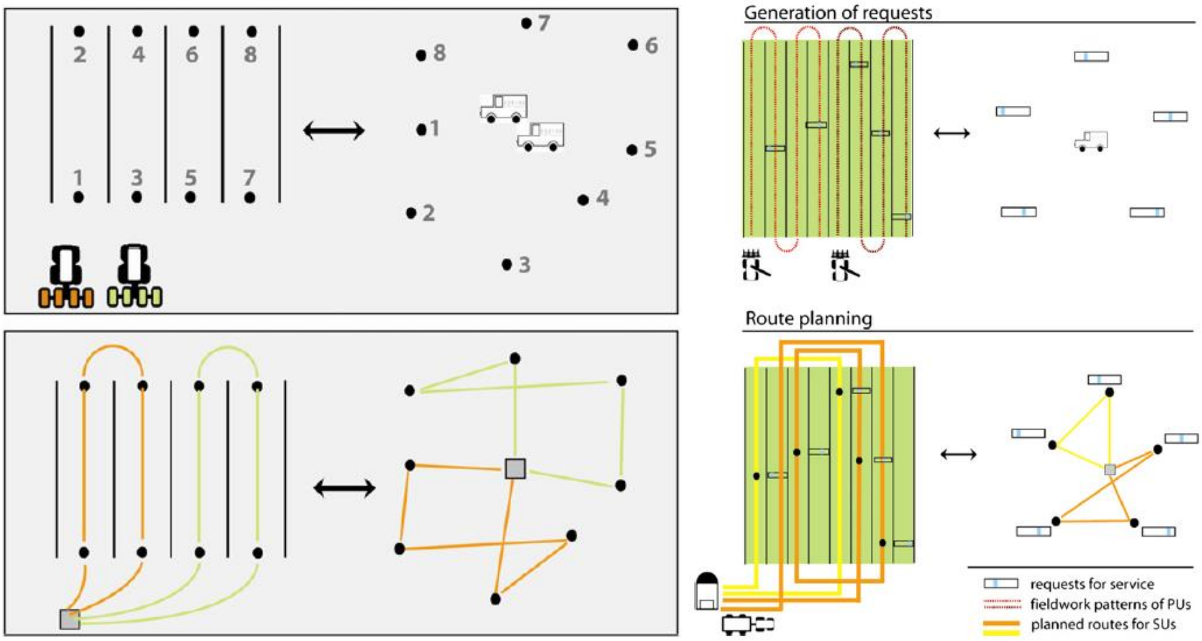

Figure 1. Correspondence between agricultural field operations and different VRP variants. Left sowing (from Bochtis & Sørensen, 2009) and right harvesting (from Bochtis & Sørensen, 2010).

A simpler type of agricultural field operation in regard to VRP is defined as neutral material flow (NMF) field operations. In this type of operations there is no flow of material into or out of the field, *e.g.* mowing, tillage or hay raking, in contrast with operations where refilling or emptying is necessary. Input material flow (IMF) operations are those that require a material to be transported into and distributed in the field, *e.g.* sowing, fertilising or spraying. And output material flow (OMF) operations are those that transport material out of the field, *e.g.* harvesting or hay bale collection (Bochtis and Sørensen, 2009). IMF and OMF operations can have different material demands, as they can be known beforehand, *e.g.* sowing with predefined seeds per area, estimated, *e.g.* harvest with an expected yield distribution, or completely unknown, *e.g.* variable-rate fertilisation based on on-the-go sensor data. Regarding VRP, IMF and OMF operations have capacity constraints and are also called capacitated field operations (Jensen *et al.*, 2015; Conesa-Muñoz, Pajares and Ribeiro, 2016).

Examples of optimised route planning for NMF operations have shown reductions in non-working distances between of up to 58.7% (Bochtis *et al.*, 2013) and total energy consumption savings from 3 up to 8% (Rodias *et al.*, 2017) by the use of B-patterns, which optimise the sequence of the field work tracks. A prototype tool for NMF was evaluated with recorded mowing operations and saved up to 18.4% of total travelled in-field distance, with a total distance saved of 7.5% for the 12 fields used in the comparison (Edwards *et al.*, 2017). Regarding IMF operations, a study about optimisation in fertilisation showed savings in non-productive distance between 15.7 and 43.5% and from 5.8 and 11.8% in total travelled distance (Jensen, Bochtis and Sørensen, 2015) and . Finally, OMF operations, such as harvesting operations, has attracted substantial attention in research because it involves a fleet of heterogeneous machines that influence and constrain each other spatio-temporally (Scheuren *et al.*, 2013). Examples showed time reductions of 31.64% for sugar cane harvest (Santoro, Soler and Cherri, 2017) or reduction in non-working distance ranging from 19.3 to 42.1% (Bakhtiari *et al.*, 2013). More on harvesting operations is described in the next subsection.

Besides VRP applied to optimise in-field operations, optimisation algorithms have been also applied for scheduling different types of field operations, *e.g.* scheduling farm-to-farm harvesting operations based on the TSP (Basnet, Foulds and Wilson, 2006; Plessen, 2019), scheduling farm operations as a VRP problem with time windows (Bochtis and Sørensen, 2010), scheduling a fleet of machinery for multiple field operations with capacity constraints (Orfanou *et al.*, 2013; He and Li, 2019), or optimising the scheduling of sequential field operations using tabu-search algorithms (Edwards *et al.*, 2015a).

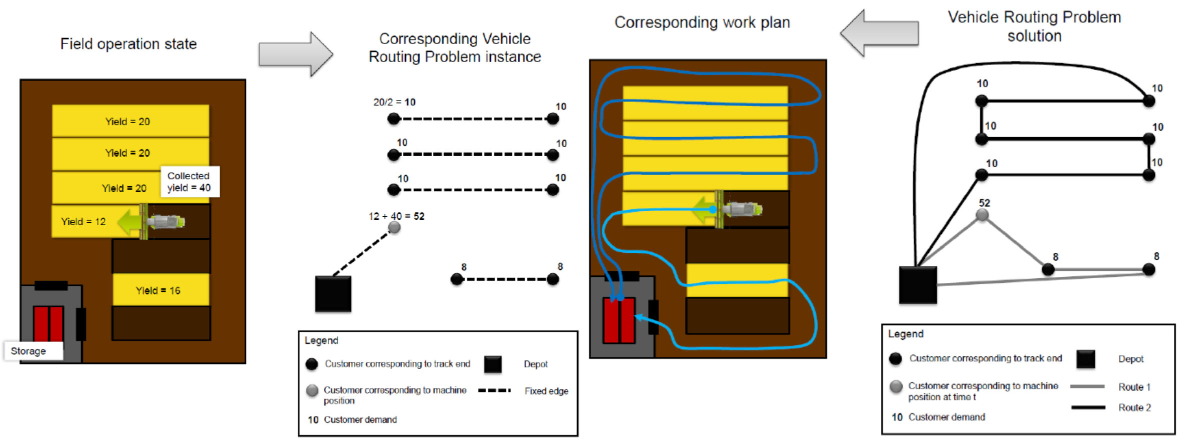

Figure 2. Example from Edwards (2015): harvesting operation transformed into VRP instance, and its solution into a work plan.

1.1.2 Harvest fleet route planning

The extensive research interest in route optimisation in harvesting operations has led to many different approaches and VRP variants to optimise this type of operation. The potential benefits of reducing the in-field travelled distance that directly affect production costs and soil compaction problems, combined with the complexity of optimising the route of a fleet of heterogeneous capacitated vehicles, are driving the increasing research attention (Bochtis and Sørensen, 2010; Jensen, Bochtis and Sørensen, 2015; Moysiadis *et al.*, 2020; Nilsson and Zhou, 2020).

Harvesting operations can be addressed by the VRP with trafficability, time windows and capacity constraints (Figure 2) (Bochtis and Sørensen, 2010; Jensen *et al.*, 2015). The trafficability constraints are defined by the tracks that cannot be driven on due to for example non-harvested crop, conflicting directions of different vehicles or in some cases due to fields with controlled traffic farming systems. The capacity constraints are caused by the load of material that a vehicle is able to carry. And the time windows constraints relate to operations with heterogeneous cooperative machines. The nodes defined by the customer in a VRP context are determined by the unloading events where a service unit, *i.e.* a grain cart, is servicing a primary unit, *i.e.* the harvester. These can be in the harvesting case static or dynamic depending on whether the unloading event occurs on-the-go or is stationary (Figure 3). In contrast, different node representations are needed for harvesting operations in plantations with equilateral triangular patterns (Hsion *et al.*, 2021).

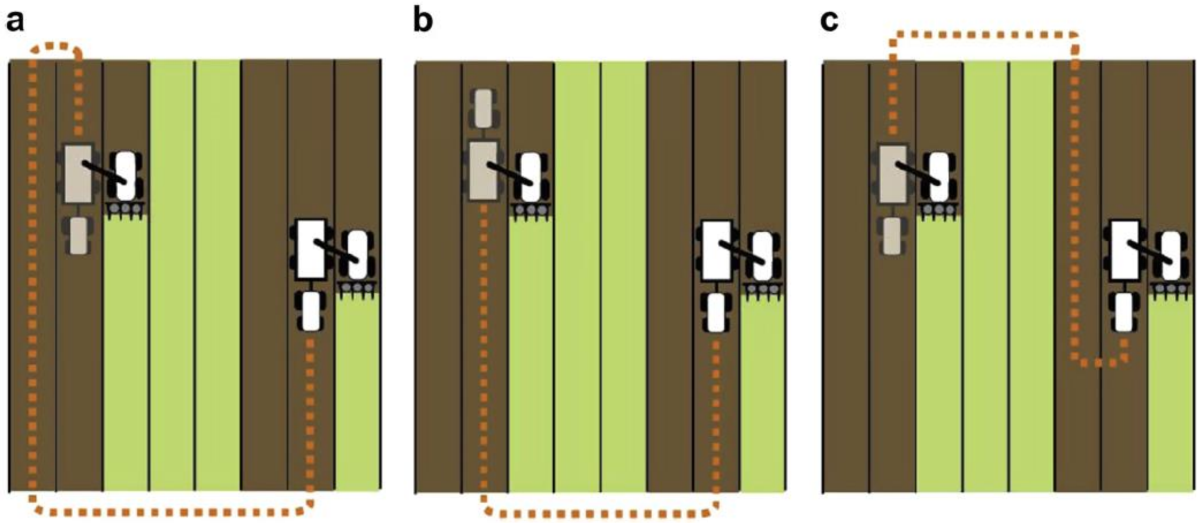

Figure 3. Examples of unloading events in harvesting operations (from (Bochtis and Sørensen, 2010)**: CTF on-the-go unloading (a), CTF stationary unloading (b) and non-CTF on-the-go unloading (c).**

The optimisation of the route planning can have many different approaches (Table 1) as well as different minimisation objectives. While many studies aim to minimise non-working distance (Bakhtiari *et al.*, 2013; Bochtis *et al.*, 2013; Conesa-Muñoz, Pajares and Ribeiro, 2016; Utamima, Reiners and Ansaripoor, 2019), others aim to minimise operational time (Cerdeira-pena, Carpente and Amiama, 2017), harvester manoeuvring time (Santoro, Soler and Cherri, 2017), energy use (Rodias *et al.*, 2017) or the risk of soil compaction (Bochtis, Sørensen and Green, 2012; Gorter, 2019).

Table 1. Examples of optimisation route planning approaches for harvesting operations.

Metaheuristic method	Minimisation objective	Reference
Tabu search + Simulated annealing algorithms	Operational time	(Cerdeira-pena, Carpente and Amiama, 2017)
Ant colony optimisation	Non-working distance	(Bakhtiari *et al.*, 2013) (Zhou *et al.*, 2014)
Evolutionary hybrid neighbourhood search	Non-working distance	(Utamima, Reiners and Ansaripoor, 2019)
Simulated annealing algorithm (Mix-opt.)	Non-working distance	(Conesa-Muñoz, Pajares and Ribeiro, 2016)
	Operational time	(Seyyedhasani and Dvorak, 2017)
Tabu search	Risk of soil compaction	(Gorter, 2019)

Most of the studies found in literature do not take into consideration a central aspect for real-world harvesting scenarios, which is dynamic rerouting (Bochtis and Sørensen, 2010; Scheuren *et al.*, 2013; Seyyedhasani and Dvorak, 2018). Dynamic rerouting or recalculation of the planned route is necessary when the execution deviates from the original solution. These unavoidable deviations can be for example caused by unexpected yield variations that change the unloading point. When comparing with static VRP, dynamic VRP is in need of new mathematical representations as the vehicles involved in the operation are already moving, and parts of the route have already been completed (Seyyedhasani and Dvorak, 2018).

Even though many optimisation solutions have been successfully applied to harvesting operations, to the author's knowledge no studies have looked into its implementation in a real-world scenario, where the planned route is presented to the vehicle operators and dynamically adapts to the deviations from the proposed plan. Nonetheless, a decision support tool for operation planning of field operations has been presented, where routes are optimised prior operation for aiding the decision making of the farm manager (Nilsson and Zhou, 2020). An essential part of a dynamic harvest fleet route planning system is vehicle and crop monitoring, as position data and tank capacities are fundamental variables in the route optimisation. Remote monitoring of harvesting operations in near real-time has been achieved by employing connected devices to the internet, where GNSS (Global Navigation Satellite System) position data and CAN (Controller Area Network) bus data are retrieved and communicated through the internet (Pfeiffer and Blank, 2015; Oksanen, Linkolehto and Seilonen, 2016).

As it has been appreciated in the studies collected in this Ph.D. project, the main focus of harvest fleet route planning systems has been operation efficiency by minimising operational time or travelled distance. The potential environmental benefits that can be achieved by employing such systems has only been slightly addressed. Rodias et al. (2017) optimised the in-field route planning of harvesting operations by minimising the total energy consumption up to 8%. With another point of view, a decision support system (DSS) that aims to minimise the risk of soil compaction was developed with the objective of planning the route based on the vehicle load and a potential risk indicator map, reducing the risk factor up to 61% (Bochtis, Sørensen and Green, 2012). The same goal but with a different approach achieved a reduction of up to 10.5% of traversed weight metres (Gorter, 2019). Moreover, the use of field maps can add new approaches to in-field route planning and optimisation, which have not yet been addressed. For example, selective harvesting, which consists on harvesting separately different field areas based on a crop quality indicator. Some approaches have been presented where the field is divided into management zones that are meant to be harvested selectively (Tozer and Isbister, 2007; Meyer-Aurich *et al.*, 2008; Whetton, Waine and Mouazen, 2018); however, these studies do not present how this type of harvest is achieved in practice. The route planning challenges that are linked to selective harvest have not been covered yet.

1.1.3 Interdisciplinary approach

Generally, VRP in harvest fleet route planning has been only addressed by the theoretical computer science point of view. This field of science has set the cornerstone for the implementation and future potential applications that need to be addressed in combination with other fields of research in an interdisciplinary manner (see Figure 4). The different disciplinary perspectives and insights can provide a deeper understanding to solve the specific problem (Macleod and Nagatsu, 2018). This means that this plurality of perceptions and goals associated with interdisciplinarity is expected to have positive impacts on the technical feasibility of the research. This has been confirmed by the strong correlation found between interdisciplinary research and the engagement in university-industry interactions (D'Este *et al.*, 2019).

Agriculture is without doubts an interdisciplinary field, which has inevitable environmental problems that are causally entwined (Koleva and Toteva-Lyutova, 2018; Macleod and Nagatsu, 2018). Interdisciplinary approaches are then also required for studying the continuous and complex problems associated with agricultural production (Vellema, Struik and Slingerland, 2020). Consequently, the apparent paradox of increasing agricultural produce without degrading more the climate and natural environment can only be addressed from interdisciplinarity. VRP applied to harvesting operations can be part of the solution but needs to be addressed with integrated perspectives from different disciplines in order to study the challenges of its practical implementation in the real-world, its effects on the environment as well as its potential applications. Furthermore, a system perspective is required in the implementation and integration of innovative technologies, such as optimised route planning. Such new technologies affect the whole system and change how the system is integrated and instantiated at different levels from diverse perspectives (Sundmaeker *et al.*, 2016). The implementation and application of harvest fleet route planning is not a mere technology transition but a system transition that involves the combination of the innovation model with the technological requirements and end-user applicability.

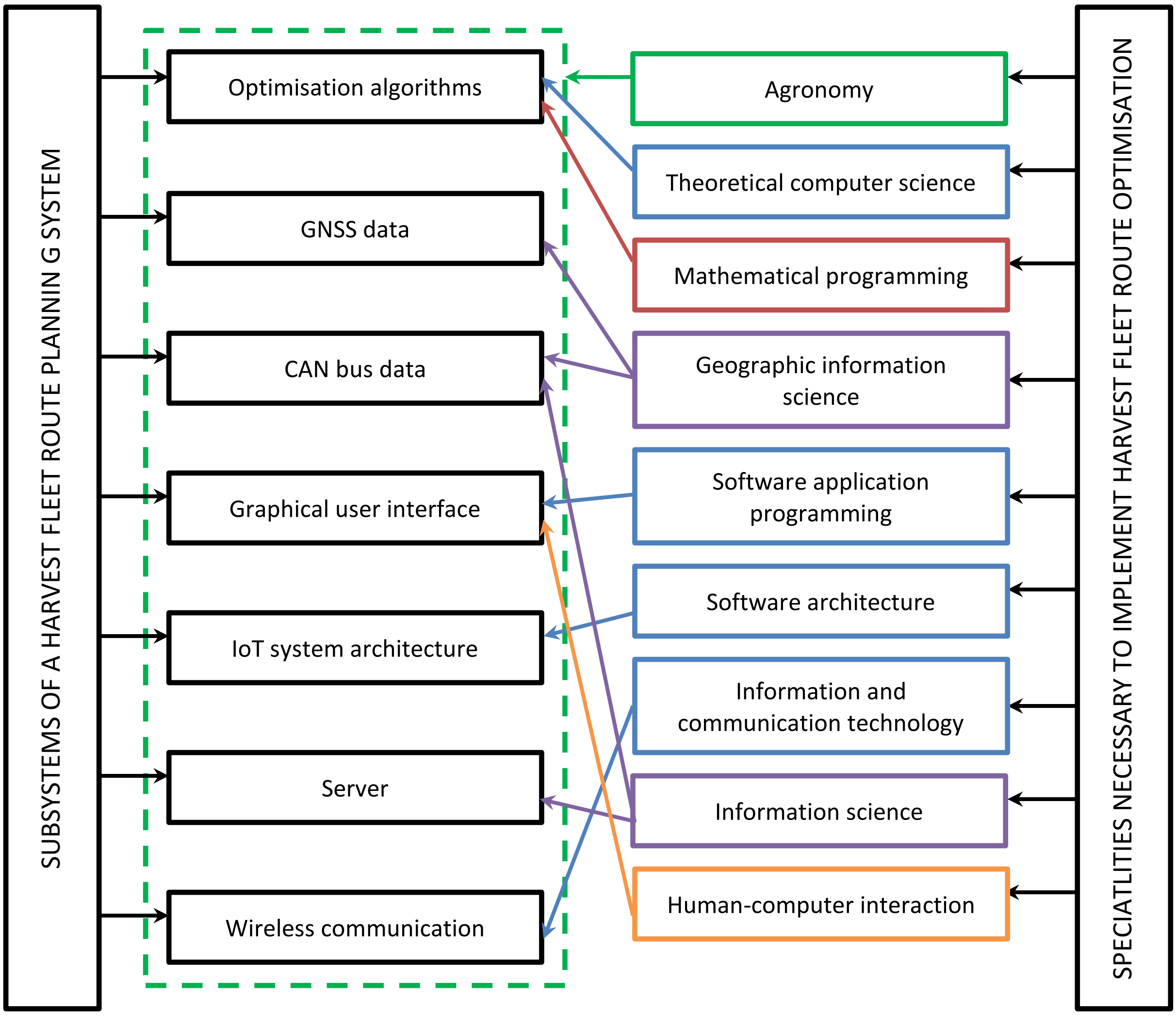

Figure 4. Subsystems of a harvest fleet route planning system and the specialities involved in its implementation.

Excluding the physical vehicles, hardware and sensors involved, the implementation of a harvest fleet route planning tool requires diverse specialities from different scientific disciplines to become a complete system (Figure 4). In most literature reviewed, these models have only focused on the optimisation algorithms, which are developed by mathematical programmer and theoretical computer science specialities. However, in practice more disciplines need to address in an integrated manner the missing technological aspects of its implementation, as well as the analytical aspects of its applications. These have not been fully addressed in literature yet. For the implementation of the tool, the architecture of the IoT system and its user interfaces are to be covered by software architecture and software application programming specialities respectively. The data retrieved and generated needs to be communicated wirelessly and processed and stored in a server, requiring specific specialities, such as information science and information and communication technologies. Additionally, the user experience is studied by human-computer interaction in order to become smooth and user-friendly. And the whole tool needs to be supervised by agronomy specialities in order to address the feasibility of its applications in field operations. The economical, marketing, advertising or adoption aspects have been deliberately omitted for simplification reasons.

The diversity of applications that a harvest fleet planning tool can have, drives the selection of optimisation approach implemented (see Table 1). The economical perspective aims to reduce operational costs by minimising travelled distances, fuel consumption or operational time, while the environmental point of view aims to reduce risk of soil compaction or total energy usage (Figure 5). From a different angle, the technological perspective focuses on the integration and practical implementation of such a tool. And the agronomic perspective centres its attention on the diversity of applications and uses of the tool (Figure 5). Additional applications can have alternative purposes such as selective harvesting that aims to increase the economic return of the farm and can be used to improve the productive capacity of a field. Finally, as robotics in agriculture is becoming a reality, optimised route planning tools are essential to navigate autonomous vehicles co-ordinately and efficiently (Kayacan *et al.*, 2015; Bechar and Vigneault, 2016; Ren and Martynenko, 2018; Moysiadis *et al.*, 2020; Villa-Henriksen, Edwards, *et al.*, 2020; Araújo *et al.*, 2021).

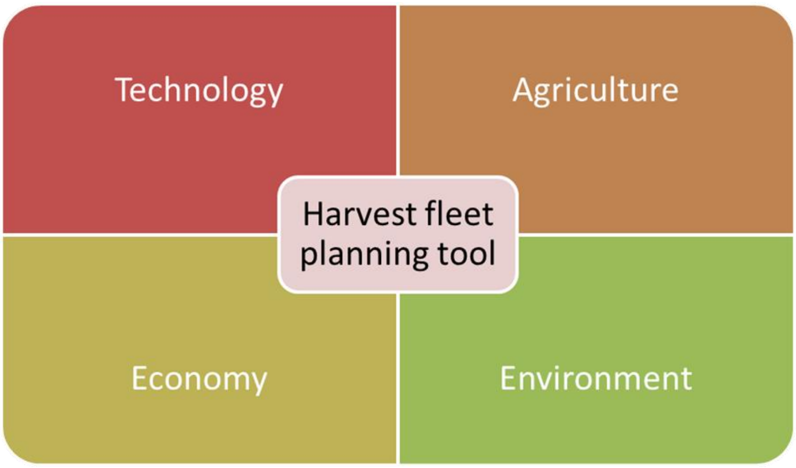

Figure 5. Confluence of perspectives of a harvest fleet planning tool.

1.2 Research gaps

From the information reviewed regarding harvest fleet route planning, several key challenges and knowledge gaps have been identified and addressed on this Ph.D. project:

- While the use of IoT technologies applied to agriculture have been widely covered, limited focus on arable farming and integration with optimised route planning has been made.
- Until now the main focus in harvest fleet route planning has been the development of the inherent optimisation algorithms, but there is a lack of technical descriptions of the physical implementation of the system.
- Even though some studies have pointed out the potential of reducing soil compaction of a harvest fleet route planning tool that aims to minimise the operational time, no studies have yet evaluated this assumption.
- The challenges of planning the route of selective harvest have not been addressed in literature, and the additional costs of the alternative route have not been evaluated.

In general, the interdisciplinary approach to harvest fleet route planning is missing.

1.3 Objectives

The main objective of this Ph.D. project was to address harvest fleet route planning from an interdisciplinary perspective by focusing on the implementation and applications of the system.

The more specific objectives aim to answer the list of key challenges and knowledge gaps already identified. The knowledge gaps are listed in the previous subsection and the objectives are outlined in Figure 6. The first objective was to review how IoT technologies are applied in arable farming and optimised route planning. This review provided the necessary knowledge to focus on the second objective, which was to address the implementation of a harvest fleet route planning tool that minimises harvest time. The third objective was to apply and evaluate the effects of the harvest fleet route planning system in reducing the risk of soil compaction. And the fourth and final objective was to apply and evaluate an optimised route planning tool for autonomous robotic selective harvesting based on protein content.

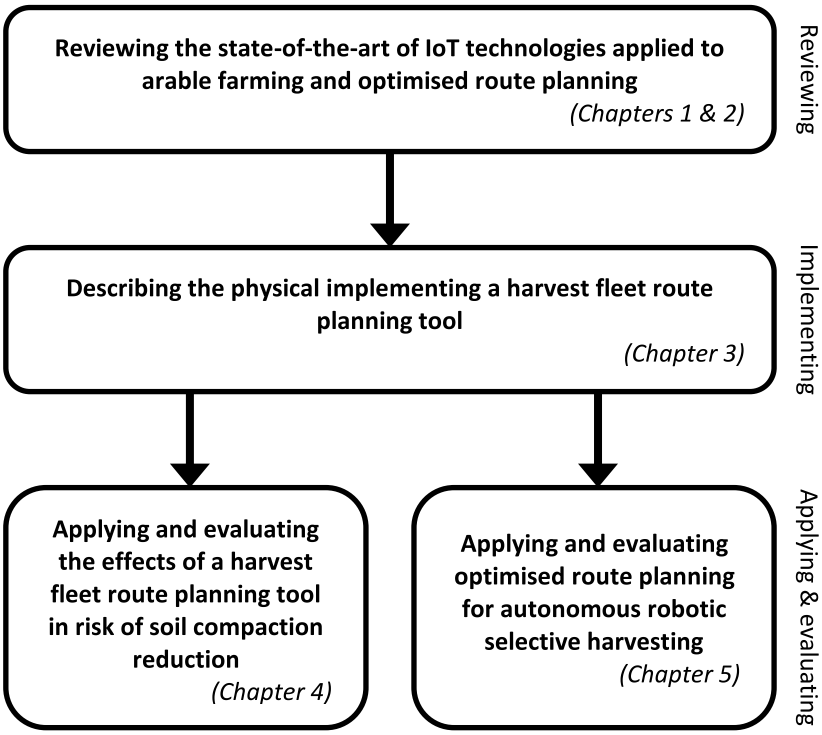

Figure 6. Research approach and thesis outline

1.4 Summary of main contributions

This Ph.D. dissertation is the result of the research funded by Agro Intelligence ApS. (AgroIntelli) and in collaboration with the Department of Engineering of Aarhus University. The project of the industrial Ph.D. programme has contributed to the field of harvest fleet route planning with an interdisciplinary approach that covers some research gaps between the theoretical computer science point of view, and the necessary considerations for the implementation of the system as well as some of its potential applications (see Figure 6).

These main contributions have been disseminated in three conference abstracts, of which one resulted in a published conference paper, one published journal review article and two more original research journal articles, one published and the other submitted. In addition, this project contributed also with a chapter in a DCA Report (Danish Centre for Food and Agriculture) with the title ‘Sustainable soil management’. An overview of the publications, their highlights, and how they have been included in the Ph.D. dissertation is presented in the subsection here below.

1.4.1 Publications

- *Internet of Things in arable farming: Implementation, applications, challenges and potential.* A review paper published in the Biosystems Engineering Journal that composes Chapter 2. The main highlights are:

- The role of Internet of Things in arable farming is reviewed.
- Internet of Things is leading arable farming to become data-driven.
- Implementation and application are described in depth.
- Challenges, corresponding solutions and potentials are discussed thoroughly.
- Attention to optimised route planning is included.

- *Internet-Based Harvest Fleet Logistic Optimisation*. A published Agricultural Engineering (AgEng) Conference paper that composes Chapter 3. The main highlights are:

  - The IoT architecture of a harvest fleet route planning tool is described.
  - The data flow of the system is addressed.
  - The communication technologies implemented in the system is described.

- *Infield optimized route planning in harvesting operations for risk of soil compaction reduction*. A published Soil Use and Management Journal article that composes Chapter 4. The main highlights are:

  - Route plans for a set of recorded fields are generated by using a harvest fleet route planning system.
  - The traffic of the recorded and optimised solutions is calculated.
  - The risk of soil compaction for recorded and optimised solutions is evaluated.

- *Evaluation of simulated grain quality-based selective harvest performed by an autonomous agricultural robot*. A submitted article to the Agronomy Journal Special Issue "The Future of Agriculture: Towards Automation" that composes Chapter 5. The main highlights are:

  - A new approach to selective harvest is presented.
  - Harvest fleet route planning is applied to create the routes for selective harvest.
  - Different theoretical scenarios for selective and conventional harvest are generated.
  - The harvest efficiency and cost-benefit analysis of the system are evaluated for the different scenarios.

- *In-field traffic management*. A published chapter in the DCA Report 'Sustainable soil management', which has been included in the Appendix.

  - The effects of in-field traffic management in agricultural operations are addressed.
  - The role of optimised route planning in sustainable soil management is described.

Chapter 2 Internet of Things in arable farming: Implementation, applications, challenges and potential

Andrés Villa-Henriksen[a,b]; Gareth T.C. Edwards[b]; Liisa A. Pesonen[c]; Ole Green[b,d]; Claus A.G. Sørensen[a]

[a] *Aarhus University, Department of Electrical and Computer Engineering*
[b] *Agro Intelligence ApS*
[c] *Natural Resources Institute Finland (LUKE)*
[d] *Aarhus University, Department of Agroecology*

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Abstract

The Internet of Things is allowing agriculture, here specifically arable farming, to become data-driven, leading to more timely and cost-effective production and management of farms, and at the same time reducing their environmental impact. This review is addressing an analytical survey of the current and potential application of Internet of Things in arable farming, where spatial data, highly varying environments, task diversity and mobile devices pose unique challenges to be overcome compared to other agricultural systems. The review contributes an overview of the state of the art of technologies deployed. It provides an outline of the current and potential applications, and discusses the challenges and possible solutions and implementations. Lastly, it presents some future directions for the Internet of Things in arable farming. Current issues such as smart phones, intelligent management of Wireless Sensor Networks, middleware platforms, integrated Farm Management Information Systems across the supply chain, or autonomous vehicles and robotics stand out because of their potential to lead arable farming to smart arable farming. During the implementation, different challenges are encountered, and here interoperability is a key major hurdle throughout all the layers in the architecture of an Internet of Things system, which can be addressed by shared standards and protocols. Challenges such as affordability, device power consumption, network latency, Big Data analysis, data privacy and security, among others, have been identified by the articles reviewed and are discussed in detail. Different solutions to all identified challenges are presented addressing technologies such as machine learning, middleware platforms, or intelligent data management.

2.1 Introduction

The global population and its food consumption is growing alarmingly fast, while climate change effects are simultaneously complicating the challenge of ensuring food security in a sustainable manner (Godfray *et al*., 2010; Tilman *et al.*, 2011). Data-driven agriculture is one of the main strategies and concepts proposed to efficiently increase the production while decreasing its environmental impact (Foley *et al.*, 2011). Data-driven technologies in general are quickly advancing with the development of the Internet of Things (IoT), and may become an important part of the future of farming (Brewster *et al.*, 2017; Jayaraman *et al.*, 2016; Verdouw, 2016a; Wolfert *et al.*, 2017). Smart Farming, also called Agriculture 4.0 or digital farming (CEMA, 2017), is developing beyond the modern concept of precision agriculture, which bases its management practices on spatial measurements largely thanks to Global Positioning System (GPS) signals. Smart farming bases its management tasks also on spatial data but is enhanced with context-awareness and is activated by real-time events, improving the performance of hitherto precision agriculture solutions (Sundmaeker *et al.*, 2016; Wolfert *et al.*, 2017). Additionally, Smart Farming usually incorporates intelligent services for applying and managing Information and Communication Technologies (ICT) in farming, and allows traverse integration throughout the whole agri-food chain in regards to food safety and traceability (Sundmaeker *et al.*, 2016). IoT is therefore a key technology in smart farming since it ensures data flow between sensors and other devices, making it possible to add value to the obtained data by automatic processing, analysis and access, and this leads to a more timely and cost-effective production and management efforts on farms. Simultaneously, IoT enables the reduction of the inherit environmental impact by real-time reaction to alert events such as weed, pest or disease detection, weather or soil monitoring warnings, which allow for a reduction and adequate use of inputs such as agrochemicals or water. IoT eases documentation and supervision of different activities as well as the traceability of products, improving the environmental surveying and control in farms from the corresponding authorities.

The IoT concept was introduced by Kevin Ashton in 1999 in relation to linking Radio-Frequency Identification (RFID) for supply chains to the internet (Ashton, 2009), but has no official definition. It implies, however, the connection of a network of "things" to or through the internet without direct human intervention. "Things" can be any object with sensors and/or actuators that is uniquely addressable, interconnected and accessible through the world-wide computer network, *i.e.* the Internet. The application of IoT in agriculture is advantageous because of the possibility to monitor and control many different parameters in an interoperable, scalable and open context with an increasing use of heterogeneous automated components (Kamilaris *et al.*, 2016), in addition to the inevitable requirement of traceability. As a result of IoT, agriculture is becoming data-driven, *i.e.* making informed real-time decisions for managing the farm, reducing uncertainties and inefficiencies, and as a consequence reducing its environmental impact.

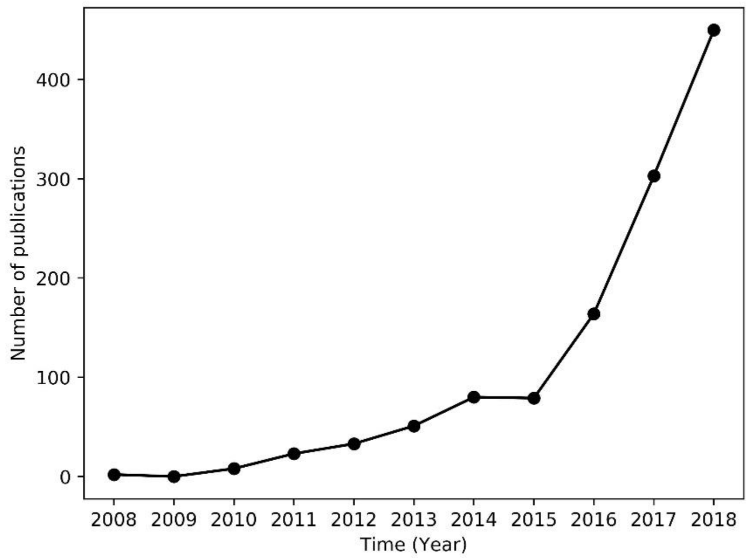

Figure 7. Number of publications per year retrieved from SCOPUS with the following searching criteria: (Internet of things OR IoT) AND (agriculture OR farming).

The application of IoT in agriculture, also called Ag-IoT (Zhai, 2017), AIoT (Zou and Quan, 2017), or IoF meaning Internet of Farming (Alahmadi *et al.*, 2017) or Internet of Food and Farm (Sundmaeker *et al.*, 2016; Verdouw *et al.*, 2017), has received exponentially increasing attention in the scientific community (Figure 7). Even though the publications are mainly dominated by Asian scientists (Talavera *et al.*, 2017; Verdouw, 2016a), in Europe several large scale international pilot projects, such as IoF2020 (Sundmaeker *et al.*, 2016; Verdouw *et al.*, 2017), AIOTI (Pérez-Freire and Brillouet, 2015), SmartAgriFood (Kaloxylos *et al.*, 2012), SMART AKIS (Djelveh and Bisevac, 2016), or more recently SmartAgriHubs (Chatzikostas *et al.*, 2019), are aiming to implement IoT technologies in the agricultural industry in Europe. Similar projects elsewhere include the Accelerating Precision Agriculture to Decision Agriculture (P2D) project in Australia (Zhang *et al.*, 2017), which complement additional major investments with the aim to help farmers convert to smart farming (Higgins *et al.*, 2017; Pham & Stack, 2018).

Several reviews have been done about IoT in agriculture in the relatively short time period where publications about the subject have emerged (Ray, 2017; Stočes *et al.*, 2016; Talavera *et al.*, 2017; Tzounis *et al.*, 2017; Verdouw, 2016a). In addition, review papers have been published with a focus on specific subjects related to IoT applied in agriculture, such as Big Data (Kamilaris *et al.*, 2017; Wolfert *et al.*, 2017), modelling (O'Grady and O'Hare, 2017), Wireless Sensor Networks (WSN) (Jawad *et al.*, 2017), food supply chain (Ramundo *et al.*, 2016), Internet of Underground Things (Vuran *et al.*, 2018), chemical wireless sensors (Kassal *et al.*, 2018), or Farm Management Information Systems (FMIS) (Kaloxylos *et al.*, 2012; Fountas *et al.*, 2015). However, to the authors' knowledge, no review exists focusing on arable farming, which has specific characteristics and challenges that differ from those in a controlled environment, *i.e.* greenhouses, or permanent crops such as fruit orchards. Arable farming poses particular challenges due to:

- much larger farm sizes, which affect the design of the sensor networks, the data processing, analysis and extrapolation of limited stationary sensor data, and the consequent decision making in regards of actuators, vehicle logistics, etc.;
- the larger farm sizes also imply that spatial data has a central role in arable farming, affecting the data processing, decision making and precision machinery employed to address in-field variability not at plant level as in most permanent crops, but at subfield level with automatic recognition and actuation (Zude-Sasse et al., 2016);
- higher use of mobile sensors and other devices on vehicles, which have specific challenges. While other cropping systems may also use sensors and devices on operating machinery, arable farming often requires a fleet of vehicles to operate co-ordinately. This creates issues especially regarding network infrastructure (Martínez *et al.*, 2016), *e.g.* connectivity of the moving things to the cloud that rely mainly on mobile networks, or vehicle to implement communication, which implies real-time interoperability between machines and devices from different manufactures (Peets *et al.*, 2012);
- larger amounts of heterogeneous spatial data generated at different rates and from very disparate sources: stationary sensors, moving vehicles and implements, satellites, data from web services, etc., which need to be intelligently integrated;
- highly varying and uncertain environmental conditions, as annual crops are more susceptible to weather changes and other external factors than permanent crops, which are more resilient mainly due to their deeper roots (Zude-Sasse *et al.*, 2016), or crops in controlled environments. This obligates the IoT system to handle both spatial and temporal data increasing the complexity of the data processing as well decisions based on the data collected.
- more diverse types of field tasks per growing season in arable farming, from soil preparation and crop establishment, through highly varying plant nursing tasks, to coordinated harvest, which increase the complexity and also the risks.

The IoT in agriculture is a fast-developing field, which can make reviews becoming obsolete quickly. This challenge can be overcome by focusing with a critical view on the general principles, main application areas and identify the limitations and challenges. Summarising, the aim of the paper is to provide an up to date novel analytical review of the role of IoT in arable farming, being the specific objectives the following:

- Provide an overview of the current situation of IoT technologies deployed in arable farming. Focussing on the current use of communication technologies and protocols, the generation and analysis of data, and IoT architectures.
- Outline the different applications and capabilities of IoT in arable farming.
- Investigate the main challenges encountered by IoT enabling technologies applied to arable farming.

- Present key potential fields of application where IoT could be employed, as well as future directions of the current trends.

The remaining part of this paper is structured as follows: Section 2 describes the methodology used in this review paper. Section 3 provides an overview of the state of the art of IoT technologies used in arable farming; Section 4 presents an outline of the current and potential IoT-based applications in arable farming; Section 5 discusses the challenges and solutions found in its implementation; and lastly, the review closes with a concluding Section 6 where future directions are summarised.

2.2 Review methodology

In order to address the specific objectives exposed above, the literature listing from the SCOPUS database of the last 11 years has been reviewed. More precisely, the timeframe investigated ranged from 1 January 2008 to 31 December 2018, selected as the whole period where any literature subjects about the subject turned up in the studied database. SCOPUS as a key peer-reviewed research literature database was selected as the primary literature source. The specific keywords used in the search criteria where: *(Internet of Things OR IoT) AND (agriculture OR farming)*. To ease the searching process, the keywords needed to be present in at least the title, abstract, highlights or keywords. Additionally, the articles had to be published in English.

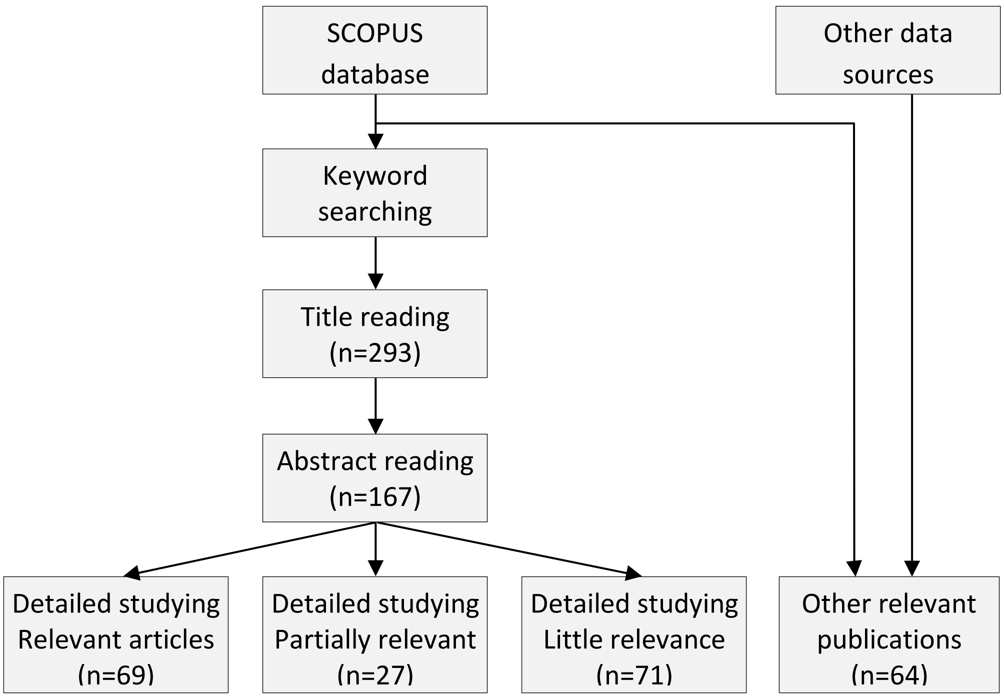

Figure 8. Reviewing procedure tree diagram.

Articles concerning greenhouse, livestock or permanent crops were excluded from the survey, as were supply chain related articles. However, issues concerning traceability at farm level were included.

The survey was performed in a systematic manner following three steps (see Figure 8):

- Firstly, a list of 1193 articles was retrieved from the database according to the searching criteria mentioned above.
- In the second step, by reading the titles any article that was clearly not related to arable farming was excluded, leaving a list of 293 articles.
- In the last step, a second screening by reading the abstracts was made, where articles outside the focus of this review were omitted. After this step, 167 articles were studied in detail, from which 69 articles were considered relevant, 27 as partially relevant, while the rest were considered of little relevance. Relevance concerned mainly the connection of the article to the subject studied. The content of a relevant article addresses directly the application of an IoT technology in an arable farming scenario. A partially relevant article studies a certain IoT technology in agriculture in a broader sense. In the distinction made regarding little relevant articles included off-topic, lack of novelty, as well as non-peer-reviewed articles that lacked scientific rigour, *e.g.* ambiguous information or absence of materials or methods description.

The final 167 articles studied included: 77 journal papers, 88 conference papers and 4 book chapters, of which 19 were review papers. The final list of articles was complemented with other publications that expanded on some of the IoT related subjects and technologies mentioned on the studied articles, and did not contain the specified keywords. These were found by a targeted search of specific subjects. Lastly, in each article of the final list there was given a special focus on the IoT technologies employed, the applications, the challenges encountered and, finally, on potential future perspectives.

2.3 IoT implementation in arable farming

IoT is recently gaining momentum in the farming industry as it can fulfil the urgent necessity for interoperability across brands, scalability and traceability (Kamilaris *et al.*, 2016). Different technologies are implemented as IoT is still evolving, adapting to the great diversity of uses. To cover the range of technologies, protocols, standards, etc. employed, this review is addressing the IoT layers in its architecture. Three layers normally describe the architecture of the IoT in the literature reviewed (Ferrández-Pastor *et al.*, 2018; Khattab *et al.*, 2016; Köksal & Tekinerdogan, 2018; Na & Isaac, 2016; Tzounis *et al*., 2017; Verdouw, 2016a), though some authors divide it into more layers (Ferrández-Pastor et al., 2016; Ramundo et al., 2016; Ray, 2017; Talavera et al., 2017; Wang et al., 2014), depending on their definitions. More than three layers can especially be relevant in IoT systems with edge or fog computing, where an edge/fog computing layer can be considered in between device and network layers (Ferrández-Pastor et al., 2016). Even if the naming of the layers also varies depending on the author, there is nonetheless a general trend to divide the layers into device, network and application layers (Figure 9). Thus, this has been the adapted structure in this review. The device layer consists of the physical objects (things) that are capable of automatic identification, sensing or actuating, and connecting to the internet. The network layer communicates the data to a gateway (or proxy server) to the internet (cloud) by the use of communication protocols. And the application layer typically stores and facilitates access to the processed/analysed information to the end-user.

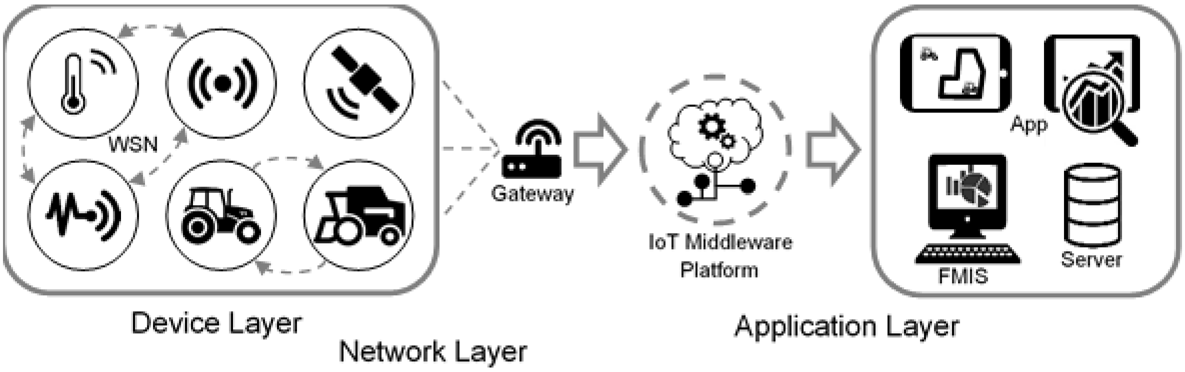

Figure 9. IoT architecture represented by device, network and application layer, in which the middleware platform is not always present.

The collected data experience diverse stages during its transition from sensors to cloud, interfaces, and occasionally actuators, which have considerable influence in the technologies applied in an IoT context. Six main stages regarding data flow have been identified in the literature reviewed: sensing/ perception, communication/ transport/ transfer, storage, processing, analytics, and actuation and display (**Figure** 10). The order of the stages is different depending on the IoT setup employed and the computing techniques used, *e.g.* fog and edge computing processes the data before communicating it to the cloud, an example of its application in precision farming can be found in Ferrández-Pastor *et al.* (2016); while cloud computing processes the data in the cloud, examples of this can be found in (Hernandez-Rojas *et al.*, 2018; Na & Isaac, 2016). Nonetheless, sensing/perception is normally the first stage, where data is captured by sensors, then the data can follow different paths and does not necessarily go through all the steps listed. In summary, IoT data is identified to be gathered or generated through three main processes: machine generated, which come from sensing devices; process-mediated, *i.e.* commercial data coming from business processes; and human-sourced, recorded by humans and digitalised later on (Balducci *et al.*, 2018). These different sources have an influence on how to process, analyse and use the data in IoT solutions, which need to be taken into account in the overall data acquisition planning process.

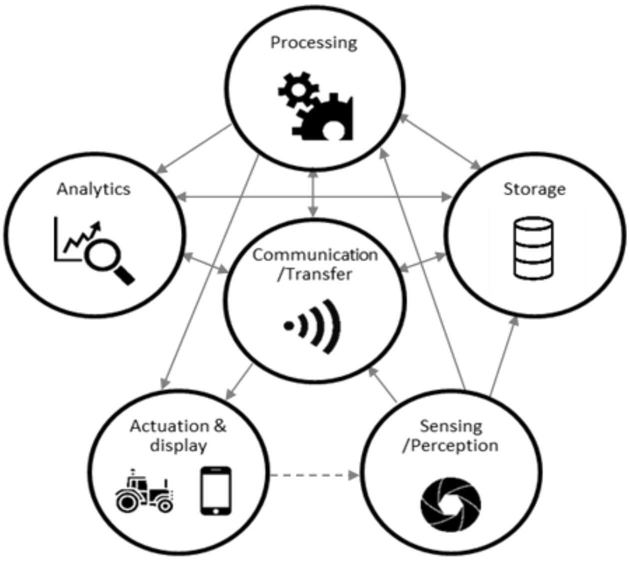

Figure 10. Different agricultural data flows in arable farming.

2.3.1 Device layer

As mentioned above, the device layer consists of the physical objects (things) that are capable of automatic identification, sensing or actuating, and providing connection to the internet. Sensor devices measure and collect one or more parameters automatically and transmit the data wirelessly to the cloud. And, when the devices turn actuators, they generally, in turn, receive data from the cloud in order to activate or deactivate some mechanical component, *e.g.* a valve in an irrigation system. The device layer is also often called perception layer (Tzounis *et al.*, 2017; Zou and Quan, 2017), sensing layer (Wang *et al.*, 2014; Na and Isaac, 2016), or physical layer (Ramundo, Taisch and Terzi, 2016; Talavera *et al.*, 2017). The devices are constituted by a transceiver, a microcontroller, an interfacing circuit and one or more sensors and/or actuators. The sensor measures a physical parameter, *e.g.* air temperature that is interpreted and transformed into an equivalent analogue signal, *i.e.* electric voltage or current, which is then converted by the interfacing circuit, *i.e.* Analogue-to-Digital Converter (ADC) into a corresponding digital format. Afterwards, the microcontroller, sometimes also in the form of microprocessors or single-board computers (Talavera *et al.*, 2017), collects the data in digital format from one or more sensors through the ADC, and sends it to the transceiver, *i.e.* a wireless communication module, which communicates the data to a gateway. A comparison of microcontrollers and single-board computers used in IoT in agriculture can be found in Ray (2017). In the case of edge computing, the microcontroller or single-board computer processes the data from one or more sensors before communicating it, with the intention of, for example, reducing the amount of data to be transferred to the cloud and accelerating the data processing (Ferrández-Pastor *et al*., 2016; Sundmaeker *et al*., 2016). In fog computing the data is processed in the local area network level, *i.e.* in a fog node or IoT gateway (Ahmed et al., 2018; Ferrández-Pastor et al., 2018). In case of employing an actuator, the signal is received by the transceiver, communicated to the microcontroller, which is then converted to analogue signal by a Digital-to-Analogue Converter (DAC), *i.e.*

the interfacing circuit, or to a digital signal by a Digital-to-Digital Converter, and finally interpreted by the actuator, that acts in accordance to the signal received.

In arable farming, when agricultural machinery data is used, *i.e.* data from sensors and devices mounted on tractors and other agricultural machinery, the data in digital format is normally collected and accessible through the Controller Area Network (CAN) bus in the machine, although in some cases some data is accessible through other ports (Oksanen *et al.*, 2016; Peets *et al.*, 2012). Machine and operator performance information is accessible through the Machine and Implement Control System (MICS) of the machine, which can also be accessed through the CAN bus data. MICS data are used to allow machinery operators and farm managers to monitor and potentially improve the efficiency of their machines, by employing *e.g.* smart alerts or recommendation systems (Pfeiffer and Blank, 2015). Global Navigation Satellite System (GNSS) data, *e.g.* Real Time Kinematics GPS (RTK-GPS), is often also available through the CAN bus port, which allows, among others, vehicle monitoring and dynamic optimised route planning (Edwards *et al*., 2017; Villa-Henriksen *et al.*, 2019).

Many different sensors and actuators are employed in arable farming. The type of device used depends on the purpose of the system in addition to the technologies implemented in the system. And the number of devices is steadily increasing. The number of IoT device installations in farms is expected to increase globally from 30 million installations in 2015 to 75 million in 2020. Furthermore, data points generated per day and farm are expected to increase from 190000 in 2014 to over half a million by 2020 (Meola, 2016). It was also estimated that by 2018 there would be 10 billion IoT devices employed in agriculture. However, the great amount of data generated is often unused or underutilised (Bennett, 2015), *e.g.* in countries like Denmark with a relative high ICT adoption in farms, only 2-5% of farmers worked in 2016 actively with the data generated (SEGES, 2016). Even if data usage is still relatively low it is expected to increase rapidly (Bennett, 2015; Wolfert *et al.*, 2017; World Bank, 2017) An overview about how they are implemented for different purposes is presented in the Applications section.

2.3.2 Network layer

The network layer communicates initially the data to an intermediary platform and eventually to the internet (cloud), and from there to, for example, employed actuators. When the data is transferred to the intermediary platform, it typically uses wireless communication technologies, for instance RFID, WSN with Zigbee, LoRa (Long Range), etc., and more recently Near-Field Communication (NFC) (Sundmaeker *et al.*, 2016; Verdouw, 2016a; Tzounis *et al.*, 2017; Kassal *et al.*, 2018). The intermediary platform is normally an internet gateway located in the vicinity of the connected devices, including also sometimes a proxy server, where the data is collected and occasionally processed in order to send the information further to the end user through the internet by the use of *e.g.* MQTT standards, or HTML or XMPP protocols.

Table 2. Wireless communication technologies (adapted from Jawad *et al.* (2017), Ray (2017) & Tzounis *et al.* (2017))

Technology	Standard(s)	Frequency	Data rates	Range	Power
ANT+	ANT + Alliance	2.4 GHz	1 Mb s^-1	30-100 m	1 mW
Cognitive Radio	IEEE 802.22 WG	54-862 MHz	24 Mb s^-1	100 km	1 W
Bluetooth (2.0, 2.1, 3.0)	Bluetooth, IEEE 802.15.1	2400-2483.5 MHz	1–24 Mb s^-1	10–100 m	0.1-1 W
BLE	IoT Inter-connect	2400-2483.5 MHz	1 Mb s^-1	10 m	10-500 mW
EDGE	3GPP	GSM 850 / 1900 MHz	384 kb s^-1	26 km / 10 km	3 W / 1 W
GPRS	3GPP	GSM 850 / 1900 MHz	171 kb s^-1	25 km / 10 km	2 W / 1 W
HSDPA/HSUPA	3GPP	850/1700/1900 MHz	0.73-56 Mb s^-1	27 km / 10 km	4 W / 1 W
ISM/SRD860	IEEE 802.11	433 MHz, 863-870 MHz	200 kb s^-1	50 m – 2 km	Very low
LoRaWAN	LoRaWAN	868/900 MHz, various	0.3–50 kb s^-1	2-15 Km	Very low
LR-WPAN	IEEE 802.15.4 (ZigBee)	868/915 MHz, 2.4 GHz	40–250 kb s^-1	10–20 m	Low
LTE	3GPP	700-2600 MHz	0.1-1 Gb s^-1	28 km / 10 km	5 W / 1 W
NB-IoT	3GPP Rel.13	180 kHz	DL: 234.7 kb s^-1 DI: 204.8 kb s^-1	Using LTE/4G base stations	Low
NFC	ISO/IEC 13157	13.56 MHz	424 kb s^-1	0.1-0.2 m	1-2 mW
RFID	Many standards	13.56 MHz	423 kb s^-1	1 m	1 mW
SigFox	SigFox	908.42 MHz	10-1000 b s^1	30-50 km	N/A
THREAD	IEEE 802.15.4	2400-2483.5 MHz	251 kb s^-1	11 m	2 mW
Weightless-N/W	Weightless SIG	700 / 900 MHz	0.001-10 Mb s^-1	5 km	40 mW / 4 W
WiFi	IEEE 802.11 a/c/b/d/g/n	2.4, 3.6, 5, 60 GHz	1 Mb s^-1–6.75 Gb s^-1	20–100 m	1 W
WiMAX	IEEE 802.16	2 GHz–66 GHz	1 Mb s^-1–1 Gb s^-1 (Fixed) 50–100 Mb s^-1	<50 Km	N/A
ZigBee	IEEE 802.15.4	2400-2483.5 MHz	250 kb s^-1	10 m (100m)	1 mW
Z-Wave	Z-Wave	908.42 MHz	100 kb s^-1	30 m	1 mW
2G (GSM)	GSM, CDMA	865 MHz, 2.4 GHz	50–100 kb s^-1	Mobile network area	Medium
3G & 4G	UMTS, CDMA2000	865 MHz, 2.4 GHz	0.2-100 Mb s^-1	Mobile network area	Medium
5G*	3GPP, ITU IMT-2020	0.6-6 GHz, 26, 28, 38, 60 GHz	3.5-20 Gb s^-1 (peak rates 10-100 Gb s^-1)	Mobile network area	Medium
6LoWPAN	IEEE 802.15.4	908.42 MHz or 2400e2483.5 MHz	250 kb s^-1	100 m	1 mW

The use of Android smart devices or other operating systems, is increasing in popularity also among agricultural applications, as they can be employed as a gateway for 3G and 4G networks, and they frequently include other wireless communication technologies, *e.g.* Bluetooth, Wi-Fi, GPRS and NFC. They also automatically conform to communication standards and protocols, in which way interoperability is increased (Balmos *et al.*, 2016; Ferrández-Pastor *et al*., 2016; Gao & Yao, 2016; Hernandez-Rojas *et al*., 2018; Villa-Henriksen *et al*., 2019). In addition, Android and other smart devices can include GNSS and RGB camera sensors, and can relatively easily be programmed for computing data and displaying Graphical User Interface (GUI) applications being able to straightforwardly update the software if necessary. In that manner, Android and similar smart devices are represented in all three IoT layers, *i.e.* sensing in the device layer, node or gateway in the network layer, and computing data and displaying GUI in the application layer. Furthermore, the automatic software updating possibilities of smart devices allow to remotely install updates with new functionalities, bug fixes, etc. and easily improve the interoperability of the system (Ferrández-Pastor *et al*., 2016).

Many different wireless technologies have been applied for diverse purposes in agriculture, depending on economical, accessibility and capability factors. Jawad *et al.* (2017), Ray (2017) and Tzounis *et al.* (2017) presented a good overview of the specifications of wireless communication technologies implemented in IoT in an agricultural context, which have been here collected in Table 2 and complemented with information from other relevant articles (Sundmaeker *et al.*, 2016; Alahmadi *et al.*, 2017; Sinha *et al.*, 2017; Elijah *et al.*, 2018; Kassal *et al.* , 2018). The great variety of technologies, standards and frequency bands used exposes the relevant interoperability and application challenges found when applying IoT technologies. Potential communication standards for smart farming can be classified into short-range and long-range according to their communication distance, which determine their specific usability in different requirement settings. This is particularly the case in arable farming, where mobile network accessibility can be an issue in many rural areas, and where large farm sizes limit the use of some wireless technologies due to their reduced communication distance and due to their necessity to replace/recharge devices batteries on nodes over large areas. These issues are addressed in the challenges section later.

A WSN is formed by pervasive devices called motes or sensor nodes, which integrate sensors and actuators that communicate wirelessly forming a spatial network (Jawad *et al.*, 2017; Tzounis *et al.*, 2017; Hernandez-Rojas *et al.*, 2018). In a WSN, base stations act as gateway forwarding the data to the cloud. Different communication technologies support different network node architectures, *e.g.* star, tree or mesh. Depending on the application, different wireless communication technologies are employed in a WSN as each has different node architecture possibilities, data rates, ranges, standards, among others, being the use of ZigBee, LoRa, Bluetooth/BLE, WiFi and SigFox relatively common in agriculture. In arable farming, BLE has for example been employed for soil and air monitoring and irrigation control (Hernandez-Rojas *et al.*, 2018); ZigBee was for example used in a WSN for monitoring soil conditions and actuating an irrigation system (Mafuta *et al.*, 2012) or crop monitoring (Zhai, 2017); and LoRa for air and water temperature of rice paddy fields (Tanaka, 2018) or smart irrigation control (Zhao *et al.*, 2018). In order to cover larger distances, GPRS is appropriate and has been used for irrigation control (López-Riquelme *et al.*, 2017), or for remote maintenance of machinery (Miettinen *et al.*, 2006). GPRS, or other technologies, such as LTE, or 3G/4G, are also commonly used at the gateway to transmit data to the cloud. Regarding other less common communication technologies used in WSNs, RFID can be integrated into a WSN too by connecting the RFID tag readers to a radio-frequency transceiver (Costa *et al.*, 2013).

Passive and active RFID technologies are to a great extent used in agricultural research and industry (Ruiz-Garcia and Lunadei, 2011), especially for animal production (*e.g.* Kamilaris *et al.*, 2016), as well as vegetable or fruit products traceability (*e.g.* Kodali *et al.*, 2017); however, in arable farming only few examples have been found: *e.g.* RFID tags used for irrigation scheduling (Vellidis *et al.*, 2008), for agrochemical traceability (Peets *et al.*, 2009), for vehicle monitoring (Sjolander *et al.*, 2011), and even on a prototype for soil temperature monitoring (Hamrita and Hoffacker, 2005). Regarding NFC, no concrete examples of NFC used in arable farming have been found in the literature reviewed.

Finally, the latest generation of mobile communications, *i.e.* 5G, has higher data rates, large coverage areas, higher peak throughput, and also improved flexibility, which can open new possibilities and may solve some of the challenges encountered by many IoT solutions (Marsch *et al.*, 2016; Alahmadi *et al.*, 2017). 5G allows new options for monitoring rural areas with no previous infrastructure for Internet connection (Faraci *et al.*, 2018). 5G can also improve vehicle-to-vehicle or vehicle-to-anything communication in *e.g.* logistics solutions, due to its low latency and new frequency bands (Marsch *et al.*, 2016). A challenge for the 5G networks will be the great increase of devices to support once IoT becomes a standard solution not only in agriculture, but also in any sphere of everyday life.

2.3.3 Application layer

The application layer is crucial in an IoT context as it is this layer that actually adds value to the sensed and communicated data through direct controlling devices, supporting farmers decision making, etc. In this layer, several important services occur such as data storage, data analytics, data access through an appropriate Application Programming Interface (API), as well as possibly a user interfaced software application. The layer may also include middleware platforms that aid handling the heterogeneous cloud data improving interoperability.

Data storage can be cloud based, *i.e.* on multiple servers, or more local based, where data is stored in different types of databases, depending on the application and design. Even if relational databases, such as Structured Query Language (SQL) databases (Gao & Yao, 2016; Goap *et al.*, 2018; Ray, 2017; Wang *et al.*, 2014), MySQL (Kaloxylos *et al.*, 2014), or PostgreSQL (Mazon-Olivo *et al.*, 2018) are employed in some of the reported applications in the reviewed articles, non-relational databases, such as Not only SQL (NoSQL), or also SPARQL, a semantic query language based database, are gaining attention due to their flexibility and scalability, especially when dealing with Big Data. Their ability to store and manage large amounts of heterogeneous data, makes them suitable in many IoT agricultural contexts (Huang and Zhang, 2017; Kamilaris, Kartakoullis and Prenafeta-Boldú, 2017). Examples of NoSQL employed in agriculture are Cassandra (Huang and Zhang, 2017), Dynamo (Xian, 2017), HBase (Wang *et al.*, 2014; Ray, 2017) and MongoDB (Martínez *et al.*, 2016). An example of SPARQL is found in Jayaraman *et al.* (2016).

Data analytics can be achieved by cloud computing, where computer resources are managed remotely to analyse data, often Big Data, or by distributed computing, *e.g.* edge and fog computing. Cloud computing has the advantage that it provides high quality services that allow independent executions of multiple applications as if they were isolated, even if they are on the same platform, *e.g.* in data centres, which is especially relevant when dealing with Big Data (Martínez *et al.*, 2016; Tzounis *et al.*, 2017; Hernandez-Rojas *et al.*, 2018). However, cloud computing techniques mostly rely on general purpose cloud providers that do not comply with specific agricultural service requirements (López-Riquelme *et al.*, 2017) and can experience latency issues, which are not acceptable in IoT solutions where monitoring, control and analysis require fast performances (Ferrández-Pastor *et al.*, 2018). Examples of application of cloud computing related to arable farming can be found in Khattab *et al.* (2016), Na & Isaac (2016) and López-Riquelme *et al.* (2017). Khattab et al.(2016) presents an IoT architecture with a cloud-based back-end where weather and soil data is processed and analysed for automatic activation of irrigation and spraying actions. Na & Isaac (2016) describes a human-centric IoT architecture with a list of cloud services, such as language translation, data simplification or updated market price information. And López-Riquelme et al. (2017) uses FIWARE components for a cloud service for smart irrigation tasks, focusing on the benefits of using FIWARE as cloud provider. Regarding Big Data analysis and Big Data in general in an agricultural context, Kamilaris *et al.* (2017) and Wolfert *et al.* (2017) have performed respectively exhaustive reviews on the subject.

The use of IoT middleware platforms is gaining interest due to its potential for solving different challenges found in the application of IoT, especially interoperability. IoT middleware platforms try to simplify the complex communication through the cloud due to heterogeneity of devices, communications and networks, by using enablers like standardised APIs and protocols (Jayaraman *et al.*, 2016; Martínez *et al.*, 2016; O'Grady and O'Hare, 2017). Examples of these are HYDRA, UBIWARE, UBIROAD, UBIDOTS, SMEPP, SIXTH, Think Speak, SensorCloud, Amazon IoT and IBM IoT, with focus on context aware functionality; SOCRADES, GSN and SIRENA, with more focus on security and privacy; Aneka, WSO_2, PubNub, SmartFarmNet and FIWARE, with a wider services oriented approach; and projects like IoT-A, OpenIoT, or ArrowHead (Gill *et al.*, 2017;

Jayaraman *et al.*, 2015; Jayaraman *et al.*, 2016; Kamilaris *et al.*, 2016; Martínez *et al.*, 2016; Ray, 2017; Sundmaeker *et al.*, 2016). Even if all these and more solutions are found in the IoT market, an intelligent middleware solution that addresses most issues observed in smart farming successfully is yet to be implemented (Jayaraman *et al.*, 2016; Martínez *et al.*, 2016; Sundmaeker *et al.*, 2016). However, FIWARE (Martínez *et al.*, 2016; Ferreira *et al.*, 2017; López-Riquelme *et al.*, 2017; Rodriguez *et al.*, 2018) and SmartFarmNet (Ferrández-Pastor *et al.*, 2018; Jayaraman *et al.*, 2016) have been implemented effectively for precision and smart farming applications.

In order to communicate data across platforms and IoT devices, ensuring interoperability, APIs are essential. These should adapt to evolving or new standards in order to ensure a longer life span, which may become a limitation if the APIs are not updated. It is through the APIs that data is made available for the IoT applications (*e.g.* Goap *et al.*, 2018; Hernandez-Rojas *et al.*, 2018). These services may include tracing, monitoring, event management, forecasting or optimisation for agricultural activities and products. These applications related to arable farming are described in the next section below.

2.4 Current and potential applications

Multiple applications can be derived from the implementation of IoT in arable farming. These applications can always be conceptualised into the three IoT layers described previously, and are not to be confused with the application layer. Elaborations of the reviewed articles show that the applications have been differentiated and categorised as follows: monitoring, documentation, forecasting and controlling. Monitoring refers to timely sensing of very diverse parameters and is mostly the initial point of entry for other applications. Documentation covers the storing of sampled data for a posterior use in *e.g.* farm management or traceability of produces. Forecasting employs different sources of data through precisely designed analytic methods for predicting concrete events. And controlling is the result of active monitoring, where processed data is used to automatically activate and control actuators in a predefined manner. A summarising table collects all the IoT applications in arable farming described in this chapter (Table 3). Most IoT-based systems include at least two of these applications and isolated applications are seldom seen. In addition, special attention has been paid on FMIS and associated decision support to improve operations and production processes involving vehicle positioning analytics, optimisation and logistics, which are key elements in arable farming (Bochtis *et al.*, 2011; Bochtis *et al.*, 2014) and have consequently got a section of its own.

Table 3. IoT applications in arable farming.

Applications		Examples	References
Monitoring	Crop	Leaf area index	(Bauer and Aschenbruck, 2018)
		Plant height and leaf parameters	(Okayasu *et al.*, 2017)
	Soil	Moisture	(Brinkhoff et al., 2017; Kodali & Sahu, 2016)
		Chemistry	(Kassal et al., 2018)
	Irrigation water	pH and salinity	(Popović *et al.*, 2017)
	Weather	Air (T, atm and RH), rainfall, radiation, and wind speed and direction	(Yan *et al.*, 2018)
	Remote sensing	Estimating crop biomass and N content	(Näsi *et al.*, 2018)
		Irrigation scheduling and plant disease detection	(Khanal et al., 2017)
	Machinery	Vehicle position and yield data	(Oksanen et al., 2016)
		Machine performance	(Miettinen et al., 2006; Pfeiffer & Blank, 2015)
	Farm facilities	Crop storage temperature and moisture levels	(Green et al., 2009; Juul et al., 2015)
	Environment	Nutrient leaching	(Burton et al., 2018)
		Contaminants	(Severino et al., 2018)
		Emissions	(Manap and Najib, 2014)
Documentation and traceability	Machinery	Field mapping	(Fountas, Carli, C. G. Sørensen, *et al.*, 2015)
		Yield mapping for fertilisation planning	(Lyle et al., 2014)
		Soil mapping for site-specific amendment measures	(Godwin & Miller, 2003; McBratney et al., 2003)
	Remote sensing	Mapping crop development	(Khanal, Fulton and Shearer, 2017; Näsi *et al.*, 2018; Viljanen *et al.*, 2018)
		Mapping soil texture and residue coverage	(Khanal, Fulton and Shearer, 2017)
	Supply chain	Agri-food traceability	(Bochtis and Sørensen, 2014; Pesonen *et al.*, 2014)
Forecasting	Machine learning models	Forecasting max. and min. T at field level	(Aliev, 2018)
		Estimating levels of P in the soil	(Estrada-lópez *et al.*, 2018)
		Forecasting soil moisture	(Goap et al., 2018)
		Plant disease forecasting	(Aasha et al., 2017; Jain et al., 2018)
		Predicting irrigation recommendations	(Goldstein et al., 2018)
		Frost prediction	(Diedrichs et al., 2018; Moon et al., 2018)
		Forecast of harvest and fertilisation dates	(Viljanen *et al.*, 2018)
	Classical models	Soil moisture and contaminant dynamics forecasting for irrigation scheduling	(Severino *et al.*, 2018)
		Fungal disease forecast in cereals	(El Jarroudi et al., 2017; Mäyrä et al., 2018)
		Forecasting field trafficability and workability for field operations	(Edwards et al., 2016)
		DAISY soil-crop-atmosphere model	(Abrahamsen and Hansen, 2000)
		RUSLE soil erosion model	(Renard et al., 1991)
Controlling	Irrigation	Fully autonomous irrigation scheme	(Goap *et al.*, 2018)
	Machinery	Variable rate fertilisation	(Peets et al., 2012)
		Site-specific weed control	(Christensen *et al.*, 2009)
		In-row cultivation in precision seeding	(Midtiby et al., 2018)
		Adaptive route planning in field operations	(Edwards et al., 2017; Seyyedhasani & Dvorak, 2018; Villa-Henriksen et al., 2018)
	Autonomous vehicles & robots	Operations of autonomous vehicles	(Bechar and Vigneault, 2016)
		In-field obstacle detection	(Christiansen et al., 2016)

2.4.1 Monitoring

Automatic monitoring is the obvious first step in IoT applied to agriculture. Strategically placed sensors can automatically sense and transmit data to the cloud for further documentation, forecasting or controlling applications. Sensors are used to monitor crop parameters such as leaf area index (*e.g.* Bauer & Aschenbruck, 2018), plant height and leaf colour, size and shape (*e.g.* Okayasu *et al.*, 2017); soil parameters such as soil moisture (*e.g.* Kodali & Sahu, 2016; Brinkhoff *et al.*, 2017) or soil chemistry (*e.g.* Kassal *et al.*, 2018); irrigation water parameters such as pH and salinity (*e.g.* Popović *et al.*, 2017); or weather parameters such as air temperature, air pressure, air relative humidity, rainfall, radiation, wind speed and wind direction (*e.g.* Yan *et al.*, 2018). In addition, remote sensing can also be employed, *i.e.* instead of sensors placed in the field they are installed on satellites or Unmanned Aerial Vehicles (UAV). However, these measurements mostly require some form of processing and interpretation as the values sampled are not directly related to the targeted parameters. An example of monitoring through remote sensing is the estimation of crop biomass and nitrogen content by the use of hyper and multispectral images (Näsi *et al.*, 2018), or the use of thermal remote sensing, which was applied for *e.g.* irrigation scheduling or plant disease detection (Khanal *et al.*, 2017). Furthermore, agricultural machinery can also be remotely monitored, *e.g.* vehicle position and yield data (Oksanen *et al.*, 2016), or machine performance (Miettinen *et al.*, 2006). This is especially relevant with the increasing appearance of autonomous vehicles and robots in agriculture (Sundmaeker *et al.*, 2016). Finally, at farm level the storage of crops can also be monitored to ensure the correct control of, for example temperature and moisture, and avoid losses due to damages (Green *et al.*, 2009; Juul *et al.*, 2015). Environmental impact indicators should be integrated in the farm monitoring applications, so that leaching (Burton *et al.*, 2018), contaminants (Severino *et al.*, 2018) or emissions (Manap and Najib, 2014) are addressed too.

2.4.2 Documentation and traceability

Collected operations and process data once stored can be used for documentation. Documentation is usually the natural application of monitored data but it must be noted that it can also include other types of sampled data, such as manually input or documentation of performed control actions (Sørensen *et al.*, 2011). The data is stored as raw data or as processed data at different levels. Documentation is essential for decision-making, controlling or analytics, and is an indispensable element in FMIS (Kaloxylos *et al.*, 2014). Mapping is also a form of documentation where data is spatially projected onto a map. On-the-go sensors installed on vehicles and implements can be used for automated field mapping (Fountas *et al.*, 2015), *e.g.* yield mapping used for posterior fertilisation planning (Lyle *et al.*, 2014), or soil mapping for site-specific amendment measures (Godwin & Miller, 2003; McBratney *et al.*, 2003). Remote sensing can also be used for mapping crop development (Khanal *et al.*, 2017; Näsi *et al.*, 2018; Viljanen *et al.*, 2018), or soil texture and residue coverage (Khanal *et al.*, 2017). Remote sensing is becoming a popular tool for monitoring and mapping, but is still to be proven feasible for all its potential applications. When documentation data sets extend beyond the farm level so that it can be traced throughout the supply chain, it is often referred as traceability and this notion is a key element in agri-food supply chain management as a measure to satisfy, for example, consumer demands (Bochtis & Sørensen, 2014; Pesonen *et al.*, 2014).

2.4.3 Forecasting

Forecasting is one of the fundamental functions for decision making that IoT brings to agriculture. Access to "real-time" data and historical data is used for forecasting events that require some form of action for managing successfully the crop or field operation. Therefore, both monitoring and documentation are important prerequisites for enabling forecasting. Forecasting is employed as preventive measures that require some action due to a predicted event, *e.g.* weeding, irrigating or harvesting. Machine learning and scientific modelling are examples of tools employed for forecasting.

Different machine learning models have been employed, *e.g.* Artificial Neural Networks for forecasting maximum and minimum temperatures at field level (Aliev, 2018) or for estimating levels of phosphorus (P) in the soil (Estrada-lópez *et al.*, 2018); support vector regression method for forecasting soil moisture (Goap *et al.*, 2018) or plant disease detection (Aasha Nandhini *et al.*, 2017); gradient boosting for predicting irrigation recommendations (Goldstein *et al.*, 2018); Bayesian networks and random forest for frost prediction (Diedrichs *et al.*, 2018); multiple linear regression and random forest in estimating yield and fertilisation requirements for forecasting harvest and fertilisation dates (Viljanen *et al.*, 2018); or also for frost prediction using four different machine learning algorithms: decision tree, boosted tree, random forest, and regression (Moon *et al.*, 2018). A rather different forecasting approach was employed by Jain *et al.* (2018), where three different models, *i.e.* random forest, support vector machine and artificial neural network were used for forecasting diseases and at the same time for adaptive data collection from the network of nodes in order to reduce data traffic and energy consumption of the network. Summarising, IoT is allowing the sampling of big amount of data, which can be employed as training data by the machine learning algorithms to build predictive mathematical models. Machine learning is opening new possibilities for effectively forecasting events in arable farming, which might change the very nature of decision making in agriculture.

Scientific modelling has also been employed for forecasting in an IoT context, *e.g.* soil moisture dynamics and contaminant migration forecasting using soil sensor data and precipitation forecasts for irrigation scheduling (Severino *et al.*, 2018); fungal disease forecast in winter wheat (El Jarroudi *et al.*, 2017) and barley (Mäyrä *et al.*, 2018); or forecasting field trafficability and workability for field operations (Edwards *et al.*, 2016). These modelling tools have an important role in agriculture as they are conscientiously developed and validated by the scientific community, and can forecast events with which machine learning models are very limited. There is also a big potential of integrating existing and acknowledged modelling tools such as the soil-crop-atmosphere system model DAISY (Abrahamsen and Hansen, 2000) or the soil erosion model RUSLE (Renard *et al.*, 1991) to an IoT solution.

Many of these solutions can make agriculture in general, and arable farming in particular, more resource efficient, *e.g.* through smart irrigation, as well as environmentally friendly, *e.g.* by smart pest and disease management.

2.4.4 Controlling

In IoT, controlling is the result of active monitoring in an automated system, where the monitored variables are automatically adjusted to, for examples, predefined thresholds. Forecasting can also play an important role in controlling. This is, for example, the case in smart irrigation systems, where the irrigation is activated before drought damages in the crop are recognised reducing yield losses. Goap *et al.* (2018) employed real-time sensing of soil moisture and soil temperature in combination with weather forecasts to control a fully autonomous irrigation scheme. Sensors on-the-go installed in tractors and implements can as well be used to control *e.g.* variable rate fertilisation (Peets *et al.*, 2012), site-specific weed control technologies (Christensen *et al.*, 2009), or in-row cultivation controlled by plant patterns in precision seeding (Midtiby *et al.*, 2018). Controlling is crucial in smart farming as it allows the automation of systems, especially considering the operations of autonomous vehicles and robots in the fields (Bechar and Vigneault, 2016), where site-specific actions and sensing-based safety systems will play an important role, *e.g.* for in-field obstacle detection for autonomous vehicles (Christiansen *et al.*, 2016).

2.4.5 FMIS

FMIS can be defined as systems that store and process farm-related collected data and provide decision supporting tools for farm management (Paraforos *et al.*, 2016). FMIS assist farmers in the execution and documentation of farm activities, their evaluation and optimisation, as well as in strategic, tactical and operational planning of the farm operations (Kaloxylos *et al.*, 2014). FMIS are consequently systems that can encapsulate all the applications previously described, and are vital elements in smart farm management. However, the adoption of targeted FMIS to the new IoT technologies is slow. A study published in 2015 showed that most FMIS architectures used at the time, were designed in the 1980s by researchers. This may explain why most FMIS currently have a structure and an architecture that is not suitable for distributed and service oriented decision support required for supporting precision agriculture and smart farming solutions, *e.g.* 75% of FMIS are still PC-based, and functionalities regarding traceability, quality assurance and agronomic best practice estimate are still missing or in their initial development stages in most commercial FMIS (Fountas, *et al.*, 2015). FMIS are key in smart farming and they should support automatic data acquisition, monitoring, documenting, planning and decision making (Köksal and Tekinerdogan, 2018). The latest research on IoT-based FMIS is expected to become part of the commercial FMIS available in the near future and will cover different needs across the supply chain and needs of the of IoT-based agriculture as a whole, as well as complying with standards ensuring interoperability between systems. In addition, decision support systems (DDS) are essential in dealing with Big Data and assisting the farm manager in managing and decision making in tasks such as farm financial analysis, business processes or supply chain functions (Kaloxylos *et al.*, 2012; Fountas, Carli, C. G. Sørensen, *et al.*, 2015). In order to design an up-to-date FMIS, it is beneficial to use preliminarily dedicated system analysis methodologies, such as soft system methodologies (SSM) for identifying required changes and constraints and propose solutions, followed by a later hard system modelling for designing the required specifications and components of the system (Sørensen *et al.*, 2010; Fountas, *et al.*, 2015). It is also necessary to base FMIS on the cloud as it allows interconnection with diverse additional services (Kaloxylos *et al.*, 2014). This development points out the inevitable need of standardisation of APIs in order to achieve interoperability among applications and services as part of the FMIS. New technologies such as distributed management systems can also enhance to a great extent the capabilities of FMIS (Fountas *et al.*, 2015). Furthermore, the introduction of agricultural moving robots in the near future, as well as the wireless and automatic control and monitoring of agricultural machinery is also to be considered in the design and development of FMIS (Fountas, *et al.*, 2015; Paraforos *et al.*, 2016). The future FMIS will also be capable of emulating farmers different work habits, as the system will automate certain tasks previously performed by farmers, which will require additional training (Sørensen *et al.*, 2011). Consequently, it is important to provide supportive adoption and transition strategies for conventional farming to convert into smart farming (Köksal and Tekinerdogan, 2018). Examples of current FMIS employed in arable farming are offered by different technology providers: machine manufacturers, institutions or targeted private companies. Some manufacturers provide their own farm management tools, such as Agricultural Management Solutions (AMS) from John Deere, or Precision Land Management (PLM) from New Holland. Across brands some FMIS have a more local approach, *e.g.* the Dutch Akkerweb developed by Wageningen University and Research, while other commercial solutions have a global approach, *e.g.* 365FarmNet, Agworld or FarmWorks.

2.4.6 Vehicle navigation, optimisation and logistics

Navigation systems are widely used in arable farming with the successful implementation of auto-steering systems in tractors and harvesters. However, IoT-based solutions are still in its early stages. IoT-based field operation monitoring (Oksanen *et al.*, 2016) or monitoring of motor and machine performance (Pfeiffer and Blank, 2015) have been effectively implemented on harvesting operations. Commercial examples of agricultural telematics are Trimble's Connected Farm, AGCO's AgCommand, John Deer JDLink, New Holland's PLM Connect or CLAAS' telematics; however, they are all closed systems, which limits greatly the possibilities of the IoT technologies, especially interoperability (Oksanen *et al.*, 2015).

Regarding optimised route planning, pre-planning harvest operations based on field data using simulation models can improve the harvest capacity of the vehicle or fleet saving working hours as well as fuel consumption (Busato *et al.*, 2007; Bochtis & Sørensen, 2009; Bakhtiari *et al.*, 2011; Jensen *et al.*, 2012; Zhou *et al.*, 2014). However, field complexity and vehicle fleet size can become major hurdles for the algorithms employed (Skou-Nielsen *et al.*, 2017; Seyyedhasani *et al.*, 2019). The accessibility of field and harvest data can be eased by IoT technologies that allow automated data collection and sharing via common communication protocols and standards, in interoperable data formats, with compatible data model hierarchies; although, this is not always the case (Tzounis *et al.*, 2017). IoT also allows to employ cloud or fog computing to solve the high computational requirements of these route planning models (Seyyedhasani *et al.*, 2019), even though the computing can also be achieved at the edge (Villa-Henriksen *et al.*, 2018). Data communication costs, latency problems and unstable mobile connectivity may pose important challenges for route planning applications that rely only on cloud computing, making mobile edge computing more adequate and robust for these systems. Nevertheless, true IoT-based dynamic route planning is still in its infancy but gaining increasingly attention, especially with the arrival of agricultural robots (Bechar & Vigneault, 2016; Kayacan *et al.*, 2015). Concerning its application, until recently, harvest logistics has employed field sampled data, *i.e.* boundaries, obstacles, gates, etc., to optimise the route of the vehicles involved in the operation statically (*e.g.* Bakhtiari *et al.*, 2011; Jensen *et al.*, 2012), where the complete routes of all vehicles are planned a priori. Nevertheless, these plans do often not comply with real-world challenges as they do not adapt to variating inputs, *e.g.* vehicle speed changes or in-field yield variations, or to unforeseen situations, *e.g.* machine breakdowns, eventual out of field delays, non-trafficable wet spots, undefined obstacles, etc. There is consequently the need to integrate route optimisation and operation logistics in IoT systems, where the optimisation can adapt dynamically to varying input and unforeseen events. It is only in the last few years that harvest logistics really started adapting dynamically to parameters such as vehicles' behaviour or in-field yield variations (Edwards *et al.*, 2017; Seyyedhasani & Dvorak, 2018; Villa-Henriksen *et al.*, 2019).

Today, new possibilities for optimising infield operations arrive with the large amount of data available via internet, *e.g.* remote sensing data or other collected spatial data. These could be adaptive planning based on trafficability maps for reducing soil compaction or avoiding vehicles to get stuck in wet spots; or selective harvesting based on predicted grain quality maps, which is expected to increase the price of the crop harvested.

2.5 Challenges and solutions

When implementing IoT in arable farming, as well as in other contexts, diverse challenges limit or affect the performance of the systems employed. The challenges identified in the literature reviewed (Figure 11) can indicate which areas need to be taken into account when designing an IoT-based system or point out areas that require further research. However, the results presented in the figure are indicative and not necessarily describe the importance of the challenges included, especially because of the multiple applications and implementation designs that are conceivable in arable farming. Any of the challenges can become crucial in different setups, and are therefore described. In addition, all challenges can be related to or have consequences on other challenges.

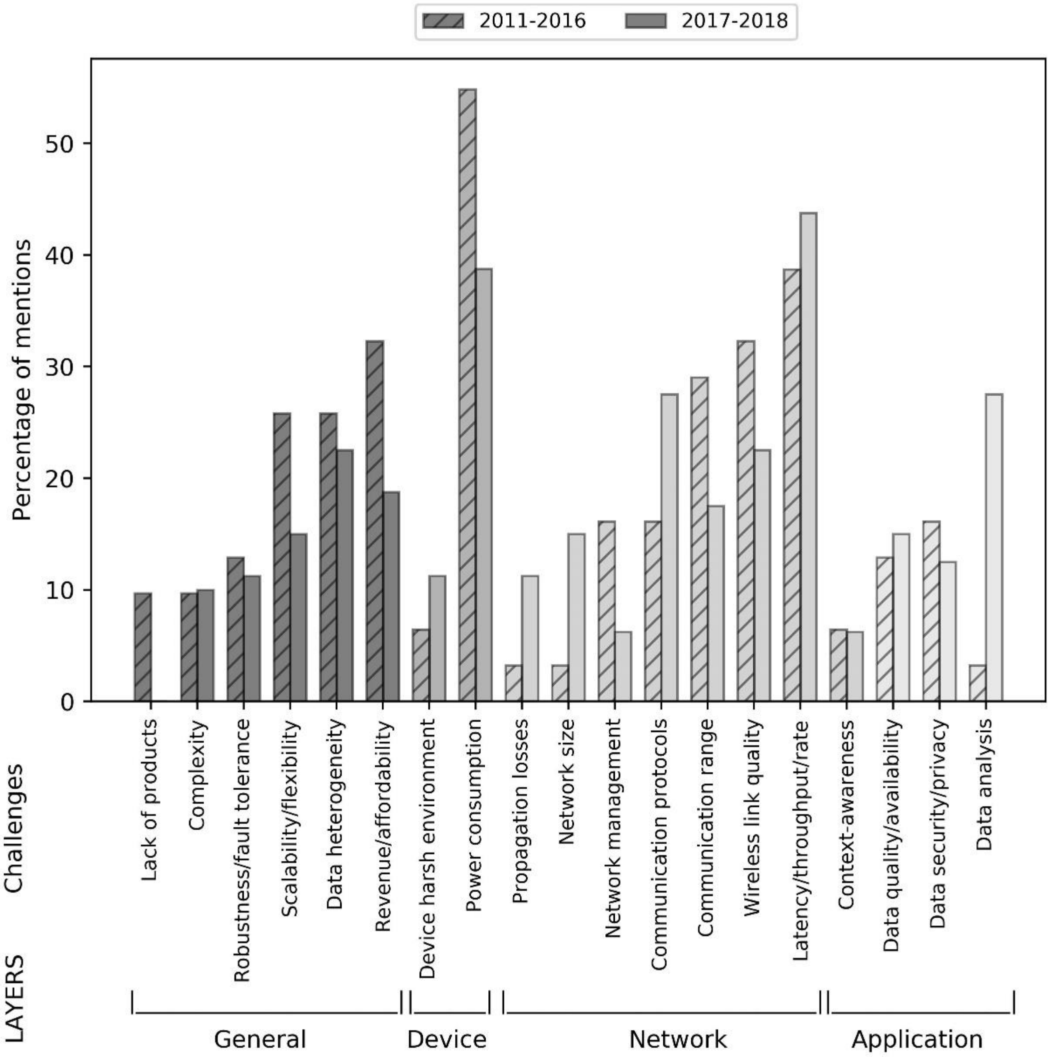

Figure 11. Percentage of challenges mentioned by the literature reviewed, divided by time periods and grouped in IoT layers.

Interoperability, in general, is a major hurdle in the application of IoT. There are different dimensions related to it: technical, syntactical, semantic and organisational (Veer and Wiles, 2008; Serrano *et al.*, 2015). Technical interoperability refers mostly to the communication protocols which affect the hardware and software components implemented. Syntactical interoperability is usually related to data formats, their syntax and encoding. Semantic interoperability concerns the interpretation of data contents, *i.e.* the meaning of the information exchanged. And organisational interoperability involves intercommunication of meaningful information across organisations regardless of information systems and infrastructures in a world-wide scale. As interoperability is such a generic term, in this section, technical interoperability has been addressed as part of the communication protocol challenge, syntactical and semantic interoperability have been included under the data heterogeneity challenge, and organisational interoperability have been described under the scalability challenge.

2.5.1 General challenges

Revenue and affordability

Often the investment for establishing an IoT-based solution is high and as such challenging for small-scale farmers, while larger farms can easier acquire IoT-based technologies when investing in new equipment (Brewster *et al.*, 2017). The uncertainty regarding required costs, *e.g.* fuel or water allocations, and selling prices of the product give little margin for many farmers for investing in new technologies (Higgins *et al.*, 2017). Trust plays an important role when investing in IoT systems, and relieving the perceived risks by demonstrating the revenues of its adoption are essential (Ferrández-Pastor *et al.*, 2016; Jayashankar *et al.*, 2018). For example, in Europe 70% of all fertilising and spraying machinery is equipped with at least one precision agriculture technology, but only 25% of farmers actually use precision agriculture components in their farms (Say *et al.*, 2017). Technology providers need to increase the perceived value by demonstrating the financial return from IoT in order to diminish the perceived risk of adoption many farmers have. Technology providers need also to provide robust tools that are aligned with farmer needs and practices in order to gain accept and trust of IoT technologies. These technologies need to reduce the workload, assist in decision making and improve the efficiency of the targeted practice. Additionally, technology providers need to develop interoperable and flexible solutions that can easily be integrated and comply with accepted standards. Governments can also incentivise the IoT adoption by policies and regulations, especially regarding documentation and traceability as ICT eases paperwork and bureaucracy. A reduction in percentage of mentions regarding this challenge (see Figure 11) could indicate that IoT is being more adopted in arable farming.

In addition, IoT is likely to reshape the arable farming business. The implementation of monitoring and control of farming operations are generating substantial amount of valuable data that are essential for the business of technology providers. The way farmers will dive into the data economy, *i.e.* connecting their data to work in vertical and horizontal networks beyond the farm, will have an effect on their business models, as well as on the business models of technology providers. The point of view of farmers business regarding IoT has not been fully addressed in the literature reviewed and will require further investigation.

Data heterogeneity

The diverse data sources and sensor manufacturers imply use of different unit systems, data structures and nomenclatures in different data formats, which result in reduced syntactical and semantic interoperability among IoT environments. Sensor data can be encoded in binary, or represented in formats such as json, xml, text (*e.g.* csv), shapefile, or even proprietary formats. The heterogeneity of data types and formats can also affect the performance of a protocol employed for communicating the information. Furthermore, this challenge becomes critical in situations such as system integration or sharing data with other systems (*e.g.* FMIS), which could imply developing data conversion tools or even redesign of the IoT setup. The use of standardised formats can help with this challenge. Some attempts have been made on producing standards or standardised formats that cover the great heterogeneity of agricultural data, *e.g.* ISO 11783 (ISOBUS) developed by the Agricultural Industry Electronics Foundation (AEF) for tractors and agricultural machinery, which is very relevant in arable farming (Miettinen *et al.*, 2006; Peets *et al.*, 2012; Fountas *et al.*, 2015; Oksanen *et al.*, 2015) or AgroXML developed by the Association for Technologies and Structures in Agriculture (KTBL) mainly for FMIS (Peets *et al.*, 2012; Kaloxylos *et al.*, 2014; O'Grady and O'Hare, 2017; Köksal and Tekinerdogan, 2018). These are now being integrated by the non-profit organisation AgGateway through the ADAPT framework and SPADE project for seamlessly communicating agricultural machinery data to FMIS, trying to enhance the existing standards and improve consequently interoperability (Brewster *et al.*, 2017). A drawback of comprehensive data models, which try to describe all attributes of agricultural data, is that they become too cumbersome to handle in many applications. Finally, the use of middleware platforms applicable in smart farming, *e.g.* FIWARE or SmartFarmNet, can also reduce the problems caused by data heterogeneity (Ferrández-Pastor *et al.*, 2018; Ferreira *et al.*, 2017; O'Grady & O'Hare, 2017; Serrano *et al.*, 2015).

Scalability and flexibility

Organisational interoperability is a key element concerning scalability and flexibility (Serrano *et al.*, 2015; Tzounis *et al.*, 2017; Verdouw, 2016b). Many of the systems described in the literature reviewed are centralised, closed, difficult to integrate in other existing platforms or difficult to implement on larger scales, different farming systems or geographical areas. They are also challenging to integrate beyond the farm level and across the supply chain in order to provide agri-food safety and traceability. The use of standardised dynamic protocols, such as SOAP protocol; cloud-based infrastructures with extensible ontologies that cover the broad and diverse agricultural production systems and environments; fast and reliable APIs, *e.g.* RESTful; and middleware platforms applicable for smart agriculture, such as FIWARE with its generic enablers, are tools that are employed to achieve organisational interoperability and make the system developed more scalable and flexible (Serrano *et al.*, 2015; Ferreira *et al.*, 2017; López-Riquelme *et al.*, 2017; O'Grady & O'Hare, 2017). Service-Oriented Architectures (SOA) bring also possibilities to effectively integrate ecosystems through open and standardised interfaces, increasing organisational interoperability (Sørensen and Bochtis, 2010; Kaloxylos *et al.*, 2014; Pesonen *et al.*, 2014; Kruize *et al.*, 2016; Köksal and Tekinerdogan, 2018).

Scalability and flexibility may also refer to WSNs in the literature, to their capacity to support increasing number of devices/nodes, being the network architecture, the gateway and protocols used the main constrains (Elijah *et al.*, 2018). This challenge has been considered under the network size challenge.

Robustness and fault tolerance
Many different factors can affect the overall robustness and fault tolerance of a system. Robust wireless connectivity is an important limitation in many setups (Oksanen *et al.*, 2016; Vuran *et al.*, 2018). In the design of an IoT-based solution dealing with faults, errors and unforeseen events need to be taken into account in order to ensure the reliability of the system. Many of these issues are related to the other challenges presented here and can be handled at the device level, but also need to be thought into the overall IoT system design (Ferreira *et al.*, 2017; Ray, 2017).

Complexity
The agricultural system is complex and can be challenging to work with. It is complex not only due to the multifaceted nature of the physical, chemical and/or biological processes in the soil-crop-air system, but also due to the technical complexity of hardware and software interacting with it. Depending on the novelty of the IoT technology implemented and the background of the developer and user, the systems can become more or less complex. For example, software and hardware incompatibilities can challenge its implementation and integration (Ferrández-Pastor *et al.*, 2016), as well as many other challenges, *e.g.* the great field task diversity in arable farming, can add complexity to the system. Technical knowledge can become a major hurdle for the implementation of IoT in farms, and it is therefore important that user-friendliness and plug-and-play basis have a high priority for the technology providers (Sundmaeker *et al.*, 2016; Zou and Quan, 2017). Complexity should be an issue for the technology provider and not for the customer.

In addition, the co-created development and implementation of IoT systems in agriculture by multi-actor approach is needed for overcoming the complexity at different levels of integrating IoT in agriculture. Good examples of this are the European Union supported research and development efforts through multi-actor large-scale pilot projects, such as IoF2020 (Sundmaeker *et al.*, 2016; Verdouw *et al.*, 2017), AIOTI (Pérez-Freire and Brillouet, 2015), SmartAgriFood (Kaloxylos *et al.*, 2012), SMART AKIS (Djelveh and Bisevac, 2016), or more recently SmartAgriHubs (Chatzikostas *et al.*, 2019).

Lack of products
In the early stages of precision agriculture and IoT in agriculture, products that integrated agronomy and ICT engineering were lacking, which hindered its adoption (Ferrández-Pastor *et al.*, 2016; Kitchen & Roger, 2007). The large scales and diversity of environments in arable farming can challenge the products used even more than in controlled environments, as they are to be modelled to describe larger areas, send information through larger distances and be exposed to harsher environments. Even if Figure 11 shows lack of references in the last couple of years, it is still relevant for some applications, *e.g.* for in-situ real-time soil nutrient sensing is still a real challenge, especially regarding calibration (Bünemann *et al.*, 2018; Marín-González *et al.*, 2013).

2.5.2 Device layer challenges

Power consumption

The use of wireless devices has major advantages over wired systems, as they are more economical to establish and can cover much wider areas. However, their power consumption with limited battery lives is a major drawback of many wireless systems, which needs to be accounted for. This issue is so important that it is the main identified challenge in the literature reviewed (Figure 11), especially for WSNs (Tan and Panda, 2010; Jawad *et al.*, 2017). The large distances to cover in arable farming make wireless devices indispensable, and solutions to reduce their power consumption and/or extend their battery life are required. These solutions can include energy harvesting, low power consumption sensors and communication technologies or power efficient management. Energy harvesting techniques can include solar cells, micro wind turbines or other interesting solutions which have been well described in Tuna & Gungor (2016) and Jawad *et al.* (2017). The power consumption of the communication technologies and sensors employed are also to be considered in the design of the IoT solution as there are big differences between devices (Balmos *et al.*, 2016; Jawad *et al.*, 2017; Hernandez-Rojas *et al.*, 2018). Choosing low power sensors and communication devices is to be taken into account when designing the IoT system (Estrada-lópez *et al.*, 2018). Low power wireless technologies, such as BLE have low power consumption but also low communication range, while Wi-Fi has somewhat higher communication range, but much higher power consumption (Table 2), however data rates and other parameters are important factors to consider too. ZigBee and LoRa have been identified as appropriate candidates for many farming applications (Jawad *et al.*, 2017). Power efficient management techniques of WSNs such as sleep/active schemes, *e.g.* duty-cycling algorithms (Ahmed *et al.*, 2018; Alahmadi *et al.*, 2017; Balmos *et al.*, 2016; Dhall & Agrawal, 2018; Temprilho *et al.*, 2018); data mitigation schemes, *e.g.* data aggregation (Abdel-basset, Shawky and Eldrandaly, 2018) or data compression (Moon *et al.*, 2018); energy-efficient routing schemes, *e.g.* mobile sinks by the use of UAVs (Bacco *et al.*, 2018; Uddin *et al.*, 2018); and other combined solutions, *e.g.* LEACH, a cluster architecture with Time Division Multiple Access (TDMA) based MAC protocol and data aggregation scheme (Kamarudin *et al.*, 2016), or dynamic power management by combining sleep/active states with dynamic data rates schemes (Estrada-lópez *et al.*, 2018). Jawad *et al.* (2017) provides a good overview and description of WSN power efficient management techniques. Lastly, techniques such as edge computing may have higher power requirements on the device, making cloud computing more desirable if power consumption is a constraint in the projected IoT solution.

On the other hand, mounting sensors and devices on agricultural vehicles and implements allows connection to the power supply of the vehicle and eliminate consequently power consumption as a limiting factor. The type of sensors that are mounted on vehicles and their implements is quite limited, being currently mainly camera-based (*e.g.* Steen *et al.*, 2012; Midtiby *et al.*, 2018). Nevertheless, there is for example potential in employing sensors on the coulters of seed-drills for mapping soil properties (Nielsen *et al.*, 2017), or other on-the-go sensors for mapping soil or crop variations (Peets *et al.*, 2012).

Device harsh environment

The natural environment where sensors and other devices are placed in can challenge greatly their functionality and longevity. Harsh weather conditions, *e.g.* high temperature variations, intense rainfall or prolonged high humidity can cause water condensation inside the devices and consequently provoke corrosion and short circuits (Bauer and Aschenbruck, 2018). While sensors and other devices situated close to the ground experience exposure to dust, mud, or even corrosive chemicals, *e.g.* agro-chemicals, which can seriously damage the performance of the device or cause its total failure (Aliev, 2018; Bauer and Aschenbruck, 2018). Chemical underground sensors are also exposed to soil chemical and biological processes that deteriorate the sensors and can mislead the measurements, requiring unfeasible maintenance and re-calibrations (Burton *et al.*, 2018; Kassal *et al.*, 2018). Choosing adequate casing that does not interfere with the functionality of the device and also tolerates the environment they are located in are essential in the design of the IoT system. Sensors are also developed for different conditions, which need to match the system minimum requirements. RFID tags have been reported to perform flawlessly under extreme conditions and environments (Ruiz-Garcia and Lunadei, 2011; Costa *et al.*, 2013); however, RFID technology is quite limited in its applications in arable farming, and suitable sensors and communication devices are therefore primarily dependent on the application and design of the IoT system.

5.3 Network layer challenges

Latency, throughput and rate

The large amounts of data generated in IoT applications do not only cause problems regarding data storage or handling, but also latency problems that reduce the throughput of the network employed. In arable farming latency problems can be of great importance in some IoT solutions, *e.g.* in WSNs where high latency imply higher power consumption of a node (López-Riquelme et al., 2017), or in dynamic optimised route planning in vehicle logistics, which require rapid responses to deviations in the route plan (Villa-Henriksen *et al.*, 2018). For reducing latency problems fog and edge computing can be employed, as these computing techniques decrease latency and network congestions (Elijah et al., 2018; Ferrández-Pastor et al., 2018), *e.g.* data compression at the edge reduces the large volumes of data communicated through the network (Moon *et al.*, 2018). In addition, the use of lightweight protocols can also reduce latency problems, *e.g.* LP4S for sensors (Hernández-rojas et al., 2018), or MQTT messaging protocol, which has a faster throughput than HTTP and works well for bandwidth limited networks (Estrada-lópez *et al.*, 2018). The communication rate is important to have in mind when planning the wireless communication technology to implement, *e.g.* 5G can handle high-rates, while SigFox or IEEE 802.15.4-based protocols are for low-rates (Jawad et al., 2017; Bacco et al., 2018). The throughput of the network affects the communication rate, and the communication rates also influences the power consumption, which have to equally be carefully considered. Fast response to events is achieved by data processing techniques such as data merging (Tanaka, 2018), data compression (Zhao et al., 2018), or dynamic and complex event processing rules for conditioning input data and immediately acting accordingly (Mazon-Olivo *et al.*, 2018). These processes can be on the cloud or at the edge, *i.e.* devices. Finally, test-bed analysis prior implementation of the network can simulate communication rates and possible latency and throughput issues (Stewart et al., 2017).

Wireless link quality

A low wireless link quality affects greatly the QoS of an IoT system as it ends in unreliable communication between nodes (Klaina *et al.*, 2018). This can be caused by multipath propagation (Ruiz-Garcia and Lunadei, 2011), background noise (Mazon-Olivo *et al.*, 2018), routing problems, *e.g.* packet collision or limited band width (Jawad *et al.*, 2017), or even by harsh environmental conditions, which affect the transceivers and the quality of the data transmitted (Elijah *et al.*, 2018). Adequate design and testing of the network are crucial for avoiding or reducing this challenge. However, techniques such as channel access methods, *e.g.* TDMA can improve the link quality by reducing packet collisions (Temprilho *et al.*, 2018). Regarding testing, the calculation of the signal strengths in real-time on the base station helps estimating the wireless link quality of a WSN when establishing the system (Klaina *et al.*, 2018). Packet loss characterisation can also be used to assess the wireless link quality of a connection (Bacco *et al.*, 2018). Additionally, blind entity identification can also help estimating the wireless link quality of a network (Mukherjee *et al.*, 2018).

Communication range

The different wireless communication technologies have very diverse ranges, which are to be accounted for when designing the IoT solution, together with other factors such as data rate, power consumption, communication protocols or costs (Table 2). In arable farming, due to the larger farm sizes and because of the employment of mobile sensors and devices on vehicles, this challenge becomes even more critical. Furthermore, relying on the approximate communication range of a wireless technology can be misleading, *e.g.* WiFi is often described to have 100 metres range, but a test analysing the packet delivery ratio regarding distance to gateway show packet losses at ≥ 60 metres (Giordano *et al.*, 2018), while using WiField devices 2.6 km range were claimed to be reached in another test having still reliable internet connection (Brinkhoff *et al.*, 2017). Testing the communication range is therefore important for some settings. In addition to the choice of wireless technology, network topology in WSNs, such as mesh topologies can also increase the communication range by using nodes to communicate with the central node (Ahmed *et al.*, 2018). Reduced range due to obstacles or topography is addressed in the propagation losses challenge later.

Communication protocols

Differences in communication protocols can cause technical interoperability issues, which can lead to connectivity and compatibility issues among the hardware and software employed (Stočes *et al.*, 2016). Network protocols are separated into diverse layers forming a protocol stack, where tasks are divided into smaller steps (Suhonen *et al.*, 2012). In the infrastructure layer, some wireless standards that define communication protocols are commonly used by different wireless technologies, *e.g.* IEEE 802.15.4, which is used by ZigBee or 6LowPAN among others, or 3GPP, which is used by GPRS, LTE or 5G among others (see Table 2). In the application layer standards such as HTTP (Kaloxylos *et al.*, 2014; Ahmed *et al.*, 2018), MQTT (Ferrández-Pastor *et al.*, 2016; Mazon-Olivo *et al.*, 2018) or XMPP (Köksal and Tekinerdogan, 2018) are commonly used in IoT applications in arable farming. Adequate protocols are especially relevant and challenging in vehicle to vehicle communication, and crucial in arable farming. Different standards in different layers require a careful planning of the whole IoT solution, as they are not always compatible and can also have an effect on the data formats used, or sensors and gateways employed (Hernandez-Rojas *et al.*, 2018). Middleware platforms can ease the integration of diverse protocols and standards by offering enough abstraction levels so that this diversity is effectively managed (O'Grady & O'Hare, 2017; Tuna *et al.*, 2017). Edge computing can also ease technical interoperability issues as a local computing layer is created to process data and create control rules before sending the data to the cloud (Ferrández-Pastor *et al.*, 2016).

Network management

Managing a WSN can imply battery change, software updates, calibration of sensors, replacement of devices and similar maintenance activities that can be very time-consuming. Smart mobile devices, *e.g.* smart phones, can make remote software updating possible, and even be used sometimes for updating some other IoT devices (Ferrández-Pastor *et al.*, 2016). Using energy efficient devices and communication techniques can also be employed to extend the battery life of devices (Jawad *et al.*, 2017). Some sensors may require recalibrations with a certain periodicity, which has to be accounted for in the projected IoT solution (Kassal *et al.*, 2018). Nonetheless, the management of the network is always to be considered when implementing IoT solutions in arable farming, where distances and number of devices/nodes can be vast.

Network size

WSN configuration schemes have a maximum number of sensor nodes per gateway that the network can handle, *i.e.* the network size. According to the analysis of the reviewed literature, network size is being identified more often in the last two years (see Figure 11), which seems to indicate new possibilities for exploiting the capabilities of WSNs. Network size depends on the wireless communication technology employed and can affect other parameters, such as data latency or scalability of the network (Balmos *et al.*, 2016). Network topologies can also influence the network size and vary from simple star network (*e.g.* Hernandez-Rojas *et al.*, 2018) to more advanced multi-hop mesh networks (Langendoen *et al.*, 2006; Ahmed *et al.*, 2018) that can increase the network size by using network nodes as relays to reach a central node and gateway. Optimisation algorithms have been used to find the best spatial distribution of WSN nodes, and therefore to assist in the optimisation of its network size (Abdel-basset *et al.*, 2018).

Propagation losses

Even though propagation losses can become a big problem for WSNs in application areas like fruit orchards and tree plantations, in arable farming hedges, trees, big rocks or sheds, as well as pronounced topography, like hills and valleys, can also block, diffract or scatter the signal reducing the communication range and cause data packet losses. Additionally, weather conditions can also degrade the wireless connectivity propagation of signals (Kamarudin *et al.*, 2016; Jawad *et al.*, 2017; Stewart *et al.*, 2017). To avoid or reduce these problems, adequate planning of the location of the sensor nodes, the antenna height, the communication protocols and the network topology is necessary. Regarding network topologies, mesh network compared to star networks can reduce propagation losses as well as increase communication range (Ruiz-Garcia & Lunadei, 2011; Kamarudin *et al.*, 2016). Moreover, propagation modelling can help planning, reduce communication tests and ensure Quality of Service (QoS) for heterogeneous wireless networks (Ruiz-Garcia & Lunadei, 2011; Kamarudin *et al.*, 2016; Jawad *et al.*, 2017; Stewart *et al.* , 2017; Klaina *et al.*, 2018).

2.5.4 Application layer challenges

Data analysis

Data analysis can in some cases become an important challenge, especially when dealing with Big Data, which is data in such amounts, heterogeneity and complexity that it need new data management techniques for its analysis (Wolfert *et al.*, 2017). Agricultural Big Data is worthless unless it is analysed; however, its analysis can be very challenging because of its volume, diversity, and quality (*e.g.* errors and duplications). This is especially challenging in arable farming, where larger amounts of heterogeneous data are generated at diverse rates and from very different sources. The literature reviewed show an increased identification of this challenges in the last two years compared with the previous 6 years (see Figure 11). This evolution might be caused by an increased access and use of agricultural Big Data in recent times (Kamilaris *et al.*, 2017; Pham & Stack, 2018). Techniques for lowering data dimensionality can ease the analysis by applying feature reduction models, which reduce data size by eliminating unnecessary data dimensions (Sabarina and Priya, 2015). Cloud computing provides the flexibility and scalability necessary for Big Data analysis, where numerous users operate simultaneously with the large and complex datasets (Gill *et al.*, 2017). Likewise, cloud platforms are perfect for storing such large amounts of data, where NoSQL databases can store and manage these large unstructured datasets (Kamilaris *et al.*, 2017). The analysis of Big Data can potentially be used for example for policy-making, reducing environmental negative impact, improve food-safety, as well as improve farm management and its production, benefiting the different stakeholders involved (Kamilaris, Kartakoullis and Prenafeta-Boldú, 2017; Wolfert *et al.*, 2017). Another facet to data analysis is the growing use of machine learning techniques, which are being used for exploring Big Data and identifying important factors and their interrelationship that affect agricultural production systems like, for example, identifying diverse patterns (*e.g.* crop development stages, weeds or diseases) as part of machine vision systems (Bacco *et* *al.*, 2018; Reshma & Pillai, 2018). In these cases, the model is built upon a sample of data, often called training data, which size and quality directly affects the final model. Choosing the adequate approach for building the model with the available data is also essential for the success of the IoT solution.

Data security and privacy

Even though data security and privacy do not constitute as a high challenge in the literature reviewed, they are certainly major concerns for the farmers, *i.e.* the suppliers of data and also end-users of the technology developed, who has little trust in service providers' use of data (Zhang *et al.*, 2017; Jayashankar *et al.*, 2018). Also, data ownership needs to be taken into consideration as raw data and processed data in IoT systems have different ownership and are accessible by different actors, affecting the necessary requirements for data security and privacy (Kaloxylos *et al.*, 2014). Research and development focus has been on sensing, processing, controlling and computing, while less effort has been devoted to solving security threats, risks and privacy (Tuna *et al.*, 2017). Other issues like cost effectiveness in for example cloud services are also affecting the security of the data, which eventually affects the whole privacy and security of the IoT solution, as low-cost services have lower security (Dhinari *et al.*, 2017). Technology providers should prioritise data security and privacy in their business models. The availability of privacy and security technologies that are dynamic enough to support the vast numbers and variety of stakeholders, as well as the complexity of its network, is still a major challenge that needs to be overcome (Verdouw, 2016b). Many solutions are being employed to reduce data security and privacy issues in each of the IoT layers of the system, *e.g.* encryption algorithms, intrusion detection mechanisms, authentication, secure routing protocols, anonymisation, etc. (Tuna *et al.*, 2017; Tzounis *et al.*, 2017). The use of middleware platforms are employed to add a security layer between network and applications, which can include confidentiality, anonymity and security to the system (Serrano *et al.*, 2015; Tuna *et al.*, 2017; Tzounis *et al.*, 2017; Rodriguez *et al.*, 2018). Additionally, newer technologies such as blockchain are aiming to solve many of the challenges related to privacy and security as well as transparency of the IoT. In agriculture, it is mainly being applied in the food supply chain (Bermeo-Almeida *et al.*, 2018). Blockchain make sense for IoT platforms where large amounts of confidential data are handled.

Data quality and availability

Some of the challenges previously described have a direct influence on the data quality, *e.g.* propagation losses, wireless link quality, robustness and fault tolerance. Anomalies detection and similar methods have been employed to identify faulty data before analysis (Lyle *et al.*, 2014; Cadavid *et al.*, 2018). The poor quality of data or its limited availability can limit many applications that involve Big Data analytics, modelling and machine learning, which can affect or even compromise the success of some IoT solutions (O'Grady and O'Hare, 2017; Wolfert *et al.*, 2017; Balducci *et al.*, 2018). In these setups, and specifically in arable farming many datasets are integrated from different sources and sensors, and the quality or scarcity of some data can become a major hurdle to overcome.

Ensuring quality and availability of the data before starting such a project is required. Even if it is not always possible to gather all the data necessary to develop models, perform correct analytics or train machine learning algorithms, scientific-based assumptions (Severino *et al.*, 2018), data augmentation (Diedrichs *et al.*, 2018) or simulated data (Wolanin *et al.*, 2019) are used to help or solve the encountered challenge.

Context-awareness (metadata)
Context-awareness is an important and distinctive feature of Smart Farming as compared to Precision Farming, because it automatically includes descriptive data from *e.g.* fields, sensors, machines, *i.e.* metadata. Metadata can include information about the date and time, node identification number, data of calibration, height and position information, or even descriptive data about an experiment objective, field, machinery, crop genotype or soil information at the sensor placement (Jayaraman *et al.*, 2015). Metadata about sensor nodes of the system are crucial for providing contextual information so that correct data analysis can be performed (Jayaraman *et al.*, 2016; Ray, 2017). Context-awareness helps computing techniques to decide what data is to be analysed, and consequently easing the computations, and the lack of this data complicate data analysis substantially. This is especially relevant in arable farming, where the system has to handle both spatial and temporal data and make decisions based on the data collected. The use of standards, formats and middleware that support metadata is therefore important to have in mind during the planning of an IoT solution (Peets *et al.*, 2009; Ray, 2017). Context-awareness facilitates new business models and strategies for data analytics and DSS software providers.

2.6 Conclusions and future perspectives

A literature review of current and foreseeable IoT technologies and systems in arable farming was carried out. This has included an overview of the state of the art of IoT technologies, an outline of the current and potential applications, and a thorough description of the challenges and solutions. From this survey, the role smart mobile phones play is highlighted, especially Android devices, which are employed in different ways for a wide diversity of applications, due to their availability, connectivity, interoperability, programmable ease and computational power. The introduction of 5G networks in the near future will enhance the capabilities of smart mobile devices due to its enhanced performance. The intelligent management of WSN as well as the capabilities of improved communication technologies can also solve some of the challenges IoT-based solutions are experiencing. The role of middleware platforms and generic enablers are expected to gain acceptance and importance, as they can solve system integration issues and interoperability challenges.

In general, regarding challenges, interoperability is a main challenge throughout the whole IoT architecture, where development and/or acceptance of standards and protocols is required to ease the issues encountered by many IoT implementations.

Furthermore, challenges such as revenue and affordability of IoT systems, the power consumption of wireless devices, latency and throughput problems during data transfer, as well as the complexity of data analysis, and data privacy and security have been identified in the reviewed literature as of high importance, and academic research should aim their resources toward solving or reducing these issues. Technology developers need to ensure that the solutions create a real benefit for the farmers and are available and applicable for both large and small producers. How IoT farm data generated will affect the business models of farmers requires further investigation as it is not fully addressed in the literature reviewed. The combination of intelligent power efficient systems with power harvesting technologies should guarantee longer battery-life of wireless devices. Computing data at the edge, *i.e.* on the devices, as well as lightweight protocols can reduce network latency and capacity/throughput problems. The emergence of Big Data is posing significant challenges for data analysis, as the complexity and heterogeneity of the huge data sets require the application of new analysis techniques than traditionally used. Techniques such as lowering data dimensionality, cloud platforms and cloud computing, including machine learning algorithms, can help in this area and new innovative solutions are expected to be developed. Finally, technology producers have to guarantee privacy and security of the data handled throughout all the layers by employing different secure methods without compromising the user-friendliness of the solutions employed. Middleware platforms can help improving the privacy and security of IoT solutions, and techniques such as blockchain can assist with privacy and security problems of IoT platforms when dealing with Big Data.

In the near future, interoperable and service oriented FMIS that are integrated in the supply chain with intelligent analytic tools will take over some of the management and decision-making tasks of farmers and advisors, which will require training for farmers to adapt to this type of FMIS. Key decision support functions include farm financial analysis, business processes, or supply chain functions, which will gain importance with Big Data analytics. In addition, DSS for vehicle logistics will grow in importance as a way to optimise field operations using route planning and sensor-based site-specific applications. Finally, the introduction of autonomous vehicles and robotics in arable farming in the near future is expected to completely change arable farming operations and production praxes requiring fully adopted IoT capabilities.

Chapter 3 Internet-Based Harvest Fleet Logistic Optimisation

Andrés Villa-Henriksen [a,b], Nick Skou-Nielsen [b], Claus A.G. Sørensen [a], Ole Green [b,c], Gareth T.C. Edwards [b]

[a] *Aarhus University, Department of Electrical and Computer Engineering*
[b] *Agro Intelligence ApS*
[c] *Aarhus University, Department of Agroecology*

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Abstract
Harvesting operations of cereal crops in a modern farming context often involves multiple vehicles, which can lead to inefficiencies and increase operational costs if they are not coordinated and used appropriately. Large distances from depot to the field, pronounced field topographies or visual barriers, *e.g.* hedges, can limit the operator's decision capabilities in terms of when and where an unload is taking place, and consequently make the operation less efficient. Moreover, the operation manager, who may be located at the farm office, does not have a clear overview of where the machines are at any given moment, or how far progressed the operation is. Therefore, cereal harvesting is an obvious case for utilising the potential of an internet-based harvest fleet logistic optimisation system - an application that assists the operators and manager in optimising the operation. The system created gives the user a live overview of the operation and vehicles involved, it assists the operator on where and when to unload, and optimises the path in the field to reduce the operational time. The concept system is described with focus on its architecture, its data flow and communication technologies used. The architecture is divided in three layers: sensor layer, communication layer, and application layer. The sensor layer consisting of a yield monitor, that measures the grain mass flow, and a GNSS receiver. The communication layer comprising the gateway. And the application layer covering the database, the data analysis and the interfaces. The system is based on Bluetooth communication between sensors and gateway and 3G/4G communication between the gateway and the cloud. Android-based mobile devices (tablets) act at the same time as gateways and interface. The system is manufacturer independent and allows any machine to be connected, so it supports the interoperability that many farmers are seeking today.

3.1 Introduction

Reduced time windows of field readiness, *i.e.* trafficability and workability, force many farmers to perform operations hastily and timely non-optimal (Edwards et al., 2016). In addition, the competitiveness of the market pressures farmers to sell their harvest at low price levels that can endanger their business. There is therefore the need of reducing production costs and optimising operation execution times as regard trafficability and workability. In terms of the latter, farmers are compelled to increase the number of vehicles involved in operations such as harvesting to increase capacity. When multiple vehicles take part in harvesting operations of cereal and other grains, it can easily lead to inefficiencies as well as increase operational costs, if they are not coordinated appropriately. However, management of such tasks can be very difficult as the manager does not have a clear real-time overview of the location of the vehicles and when and where on- and off-loadings are happening. Furthermore, the decisions of the operators are also challenged by factors such as large distances from depot to the field, pronounced field topographies or visual barriers, *e.g.* hedges, especially regarding precise time and location of unloading points. Hence, an internet-based harvest fleet logistic optimisation system can increase the efficiency of harvesting operations, as well as create documentation of yield measurements and operations. Optimising the route plan of a single machine can reduce operating distance and consequently time (Edwards et al., 2017), and these effects increase proportionally the larger the number of vehicles involved in the operation (Seyyedhasani and Dvorak, 2017).

The fast growth of Internet of Things (IoT) technologies in agriculture (Tzounis et al., 2017; Verdouw, 2016), is allowing the automatic collection, storage and sharing of data, which creates new possibilities for machine monitoring and optimisation. Wireless tracking of cotton harvesting operations has been performed using RFID tags (Sjolander et al., 2011), however, the system was offline and did not transfer the data to the internet, nor did it interpret or process the data for posterior yield mapping. Live machine monitoring and performance evaluation has been achieved connecting mobile devices by Wi-Fi communication (Pfeiffer and Blank, 2015), and even though the system performs analytics on the Controller Area Network (CAN) bus data retrieved, which is shared with the operator in the cabin, the system does not optimise the operation and relies on the decisions of the operator. In a similar manner, yield CAN bus and Global Navigation Satellite System (GNSS) data from a combine harvester has been monitored live using 3G mobile network and OPC Unified Architecture protocols (Oksanen et al., 2016), but no fleet logistics optimisation was done.

A novel application that assists operators and managers and optimises harvesting operations is presented. The harvest fleet logistic optimisation system created gives the user a live overview of the operation and vehicles involved, it assists the operator in predicting time and location of future unloads, optimises the path in the field to reduce the operational time, and documents operation performance, *e.g.* batches, for further actions and analysis. The system employs Android mobile devices for data processing, for communicating the data to the cloud using it as the gateway, and for assisting the operator during the harvest employing it as the graphical user interface (GUI). Moreover, the system includes a web service for live monitoring of the operation, as well as for visualising documented operations from the database, including batches information.

3.2 System description

The overall architecture of the system is represented by three layers: sensor layer, communication layer, and application layer (Figure 12), following the common IoT architecture employed in agriculture (Verdouw, 2016). The sensor layer includes the yield monitoring system from the combine harvester and the GNSS receiver. The communication layer comprises a Bluetooth CAN bus adaptor that transfers the data to the Android device, and the Android device is used as the gateway for transferring the information via 3G and 4G networks. Finally, the application layer is represented by the server storing the data and the Android mobile device, which computes the data and acts as a GUI, and the web service, which also provides a GUI.

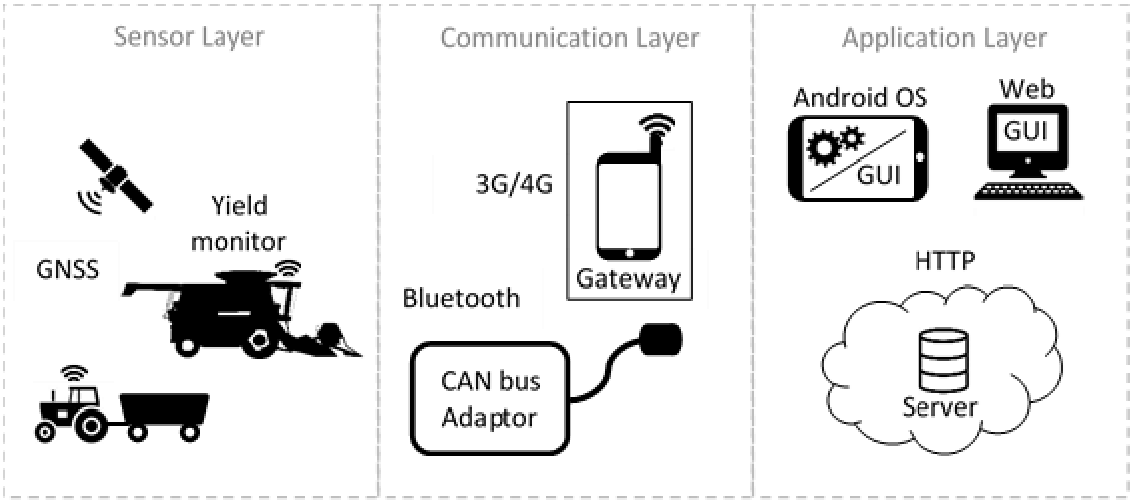

Figure 12. IoT architecture of the harvest fleet logistics optimisation system

The five elements composing the system are: a Bluetooth CAN adaptor, a harvester mobile application, a service mobile application, a web manager service and a server (Figure 13). The Bluetooth CAN adaptor is a single-board computer connected to the bus plug, which reads CAN bus messages and transmits them via Bluetooth with a rate of 1 message per second. The CAN adaptor retrieves CAN bus data coming from the following sensors: a mass flow sensor, *i.e.* an impact plate attached to a load cell; a grain moisture sensor, that measures the capacitance of the grain by passing it through two electrically conductive plates; and a GNSS sensor, *e.g.* the Real-Time Kinematics Global Navigation System (RTK-GPS) of the harvester. The harvester mobile application receives the CAN bus data via Bluetooth, performs the computations for optimising the route and loading points, and guides the operator via the GUI. The calculations optimise the route according to the field boundaries, working width, number of headlands, the behaviour of the harvester and the service units, *i.e.* tractors with grain carts, as well as the yield variations measured, so that the optimisation is an on-going process that adapts to any dynamic change in parameters. The field boundaries can be drawn in the web manager and retrieved by the harvester application in json format, or they can be recorded while harvesting the first headland track around the field, which are then stored in the database for any future further use. The service mobile application can receive GNSS data via Bluetooth from a receiver or use the inbuilt GPS of the mobile device. It also computes the route to follow according to the time and location of the unloading points defined by the harvester application, which is then communicated to the operator through the GUI. The communication between harvester and service applications elapses through the internet using 3G/4G mobile networks using HTTP requests. The web manager retrieves the position of the vehicles, which is displayed live, and the batch information of the loads, *i.e.* its original location in the field, collected time, its weight and moisture. The final component is the server, which stores the data in an SQL-based database (MySQL), which can be retrieved from the web service, as well as it handles the message communications between harvester and service mobile applications and the web service. The combination of CAN adaptor and Android device adapts the combine harvester into a "thing" in an IoT context, expanding operational capabilities.

An important challenge encountered by most IoT based systems is interoperability, not only syntactical due to the great diversity of data formats (Tzounis et al., 2017; Brewster et al., 2017; Martínez et al., 2016), *e.g.* standardised (ISOXML, agroXML, geojson, etc.), non-standardised (XML, JSON, CSV or other types of TXT), binary (shapefile) or proprietary; but also technical interoperability due to the considerable amount of different wireless communication technologies and protocols (Tzounis et al., 2017; Ray, 2017; Oksanen et al., 2016). In the case presented here, the CAN adaptor shares the data in a proprietary text file, similar to CSV file format, and the GPS data is shared and stored in the server following NMEA 0183 standards, which are both relatively easy to handle formats. Regarding technical interoperability, the use of Android smart devices has been reported to ease some of these issues, as it can easily be programmed through applications development, it can be implemented as IoT gateways for 3G and 4G communication, it can include other wireless communication technologies such as Bluetooth, WiFi or Near Field Communication, it complies with standards and protocols that ease communication, and it can also have in-built GNSS geolocation (Hernandez-Rojas et al., 2018; Gao and Yao, 2016; Balmos et al., 2016). In addition, they can have a considerable computing capacity allowing the computations to be performed on the edge, *i.e.* on the devices employed, in contrast to cloud computing. The popularity of this Linux-based operating system, developed by Google, makes it a relatively cheap solution for easily implementing IoT technologies in agriculture, and are therefore an obvious choice for the harvest fleet optimisation system presented here. The android application was programmed in Java programming language.

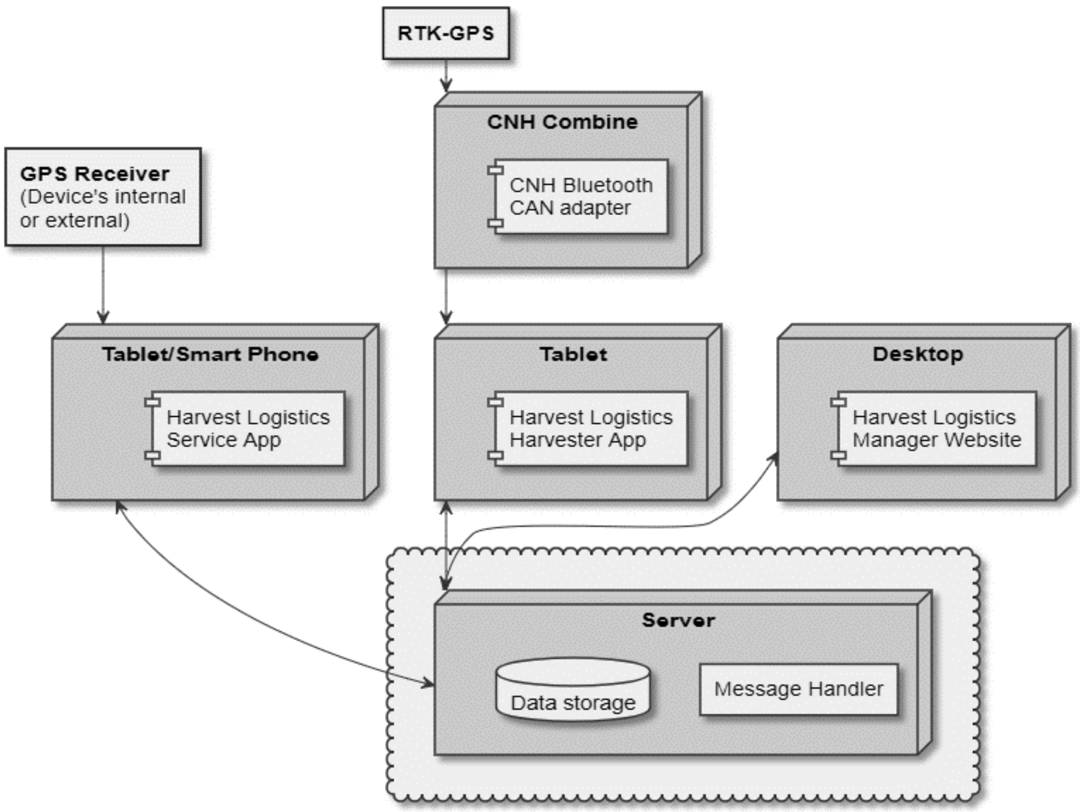

Figure 13. Deployment diagram (generated with PlantUML in Confluence)

3.3 Implementation

For testing the functionality and communication of the system, a farm in Havndal, in Jutland (Denmark) was used during their harvesting operations throughout August of 2017 (Figure 14 and Figure 15). For the operations, a New Holland CR10.90 combine harvester was serviced by two tractors with different sized grain carts with 16 and 18 tonnes of capacity, respectively. The harvester was equipped with a Samsung Galaxy S2 tablet running the harvester application, obtaining the yield and GNSS data via the CAN bus adaptor. The tractors servicing the harvester were each equipped with a Huawei Media Pad tablet running the service application, obtaining their position from a QStarz 818XT GPS receiver connected to the tablet via Bluetooth. The service application can also run with the internal GPS of the Android device; however, it was chosen to use an external GPS for higher position accuracy. All Android devices were plugged in to the power supply of the vehicle via a USB cable connected through a 12 V adaptor.

In total, the system was tested in 9 different fields harvesting diverse crops, *i.e.* rapeseed, rye, wheat and grass seed, each of the crops having different operational characteristics, *e.g.* different working speeds and yield volumes.

Figure 14. Android tablet in the cabin indicating and monitoring a load transfer into a grain cart.

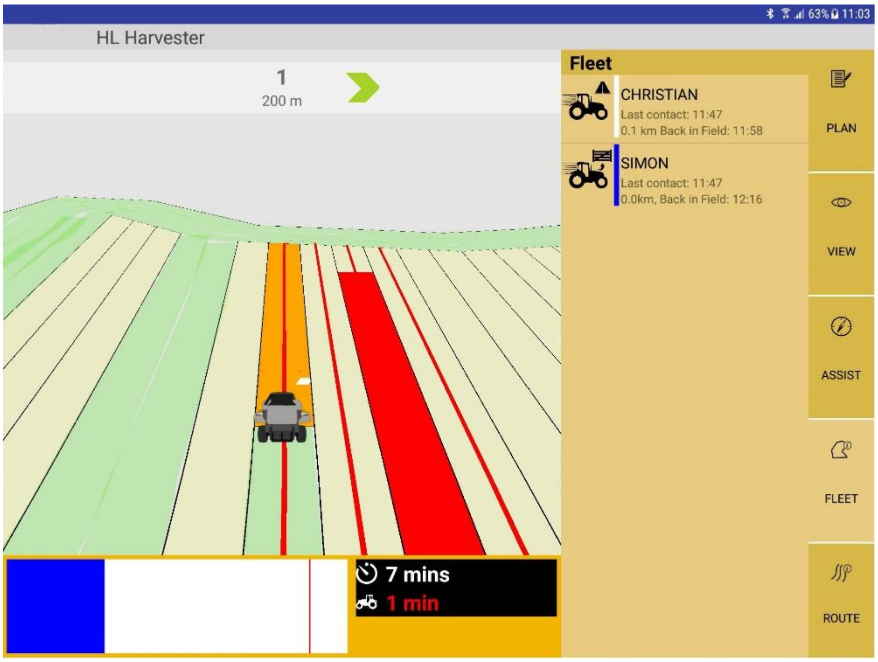

Figure 15. View of the harvester Android application showing the harvested and non-harvested areas, the unloading area, the grain tank capacity status and grain carts statuses.

3.4 Results and discussion

The system was able to retrieve position data from the external GPS in the tractors, as well as from the RTK-GPS from the harvester through the Bluetooth CAN adaptor, once the pairing and connection was established. The Bluetooth CAN adaptor was also able to transfer CAN bus data from the harvester to the harvester app without bigger issues than the yield sensor calibration, which not being properly calibrated affected the calculations of the unloading points. Some of the crops harvested had more calibration issues than others. Even if a proper calibration of the yield sensors is imperative and would be the optimal (Griffin et al., 2008; Lyle et al., 2014), many farmers do often not engage in such a task; in consequence, since most operators weigh their loads before unloading at the storage this measurement could be used as an input for auto-calibrating the harvest fleet logistics optimisation system.

The Android devices gateway functionality performed a correct communication through the message handler in the "cloud", as long as there was access to the internet via the 3G and 4G wireless communication technologies. Even though no internet connection problems were experienced, many rural areas fail to have a decent mobile network (Nakutis et al., 2016), which can limit the functionality of the system. In order to deal with internet connection problems, the system stores the last messages and computes according to them until internet connection is re-established. However, if the connection is not restored in due time, it will start affecting the optimisation, as it cannot update position and yield data. A solution could be to use the Bluetooth connection to actualise the data, when two or more vehicles are in its communication range, which is of a few meters (Jawad et al., 2017). Furthermore, it could also be possible to enhance the system with low power wide area wireless technologies that have kilometric ranges, *e.g.* LoRa or SigFox (Sinha et al., 2017).

The large amounts of data to be communicated in IoT contexts can become a major limitation, create latency problems and even occasionally imply high expenses of mobile data usage (Jawad et al., 2017; Jayaraman et al., 2016; Tzounis et al., 2017). However, frequently large amounts of the data transmitted to the cloud remain underutilised (Wolfert et al., 2017), meaning that the data transmitted could be limited. Edge computing can ease this challenge as it considerably reduces the amount of data transferred, along with easing the storage capabilities of the server (Ferrández-Pastor et al., 2016). In addition, the computations can be performed in near real-time, when done at the edge. For all these reasons mentioned, the harvest fleet logistics optimisation system successfully employs edge computing, being able to adapt rapidly to yield variations in the field, changes in operation speed, changes in the transport vehicles position or deviations from the optimised route proposed. The data traffic of the mobile application is sending approximately 2.9 KB s^{-1} and receiving 0.9-1.6 KB s^{-1}, after the data processing is performed. If there was no processing in the tablet and the full message strings where to be sent, the mobile application would be sending approximately 6.8 KB s^{-1} and receiving 2.4 KB s^{-1}, after office testing was made. A reduction of 57.35% of sent data was achieved. Furthermore, computing at device level not only reduces the amount of data transferred, but also considerably reduces the lag-time if the computations were made in the cloud, achieving near real-time optimisation. The downstream data to be retrieved from the server is minimised to the minimum for the system to function, *i.e.* the messages include uniquely information of the current status of the vehicle, with a rate of one message per second when the machine is moving and one message every five seconds when the machine is still. The stored data in the server was accessible during the operation, and after the operation was finalised, having as well available batch information of the different crops harvested.

Power consumption of the sensors and devices employed is often an important challenge when implementing IoT in agriculture (Ray, 2017; Tzounis et al., 2017; Verdouw, 2016), due to their reduced battery life. Nevertheless, in the case presented here, power consumption is not problematic as sensors and Android devices are plugged to the power supply of the vehicle.

A final but still very relevant issue to be mentioned is privacy and security of the data stored and transferred. The use of authentication protocols, signature and encryption schemes are necessary for ensuring data privacy and security (Tuna et al., 2017; Ranjan and Hussain, 2016; Oksanen et al., 2016; Tzounis et al., 2017). The system includes a username/password authentication procedure in the web service, and it relies on the inherent security of the tablets. Password encryption is used to reduce potential misuse as well as undesired interferences of third parties. Further work on protecting and securing data in the devices, the storage and communication of the system needs to be applied.

3.5 Conclusions

A novel application that assists and optimises harvesting operations was presented. The implemented harvest fleet logistic optimisation system provides a live monitoring of the operation and vehicles involved, and assists the operators with information about unloading time and location, as well as optimising the route, and documenting the operation. The system employs Android mobile devices due to their flexibility and scalability for overcoming challenges such as interoperability. The Android devices fulfilled the following functions: data retrieving, processing and data transferring, as well as assisting the operator through a GUI. Moreover, the system includes a web service for live monitoring of the operation, as well as for visualising documented operations from the database.

The harvest fleet logistics optimisation system could easily access the data from the CAN bus through the Bluetooth CAN adaptor, including yield monitor and GNSS data, as well as communicate the position information of the transport units assisting the combine harvester. However, the adequate calibration of the yield monitor is essential, as it affects the prediction of the load transferring points. The use of 3G and 4G mobile networks for communicating the data worked adequately but can present a major impediment in rural areas without a stable mobile network. Besides, the server stored the harvest operation data in the database, which could be monitored live or retrieved later from the database. The amount of data communicated through the internet was minimal to reduce latency problems and ensure the proper functionality of the system.

Chapter 4 Infield optimised route planning in harvesting operations for risk of soil compaction reduction

Andrés Villa-Henriksen[a,b], Nick Skou-Nielsen[b], Lars Juhl Munkholm[c], Claus A.G. Sørensen[a], Ole Green[b,c], Gareth T.C. Edwards[b]

[a] *Aarhus University, Department of Electrical and Computer Engineering*
[b] *Agro Intelligence ApS*
[c] *Aarhus University, Department of Agroecology*

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Abstract
Soil compaction is a major problem in arable farming mainly caused by the intensive traffic of heavy machinery. It affects negatively soil and crop development. Even though the first wheeling is considered the most damaging, repeated traffic deteriorates further the soil and subsoil even up to irreversible conditions. Intelligent in-field traffic planning in the form of optimised route planning is one key option to mitigate soil compaction. Currently, no comprehensive evaluation of the benefits of such methods exists. In this paper, a harvest logistics optimisation system was employed to evaluate the effectiveness of optimised route planning in reducing traffic by generating simulated operational data and comparing it to a set of six recorded fields ranging in size (2-21 ha) and shape. For the evaluation, simulated and recorded data for each 12 X 12 m grid cell within the fields were compared by analysing three variables, *i.e.* traffic occurrences, accumulated traffic load and maximum traffic load per grid cell. The results showed a reduction of the total number of traffic occurrences with a field size weighted mean of relative differences of 9.8%. A reduction of 5.6% for the accumulated traffic load, and an increase of 4.0% for the maximum traffic load. Repeated traffic was reduced in four of the six fields. Even though optimised route planning is not directly intended for traffic reduction, it can notably contribute to such mitigation efforts and adds an extra element to the overall farm strategy for soil compaction mitigation.

4.1 Introduction

Over the last decades, the industrialisation and intensification of agriculture have intensely changed arable farming (Bochtis and Sørensen, 2014). The machinery operating in the fields are increasing their capacity as a response to the necessity of producing more with lower unit production costs. This higher capacity inevitably comes with higher weight, which can result in long-term sub-soil compaction problems (Schjønning *et al.*, 2015; Keller *et al.*, 2019). This world-wide tendency is leading to poorer physical soil properties due to compaction within many arable fields that also has negative effects on crops, *e.g.* limiting the development of the roots (Bengough *et al.*, 2011; Lipiec *et al.*, 2012), affecting negatively the mineralisation of soil organic carbon and nitrogen (Neve and Hofman, 2000), and eventually cause yield decrease (Alblas *et al.*, 1994; Lipiec and Hatano, 2003; Chen and Weil, 2011; Tim Chamen *et al.*, 2015; Schjønning *et al.*, 2016; Obour, Keller, Lamandé, *et al.*, 2019), as well as the need for increased energy input in tilling compacted soils due to higher penetration resistance (Tim Chamen *et al.*, 2015; Schjønning *et al.*, 2016). Apart from these negative effects, soil compaction has negative consequences on the environment too in terms of *e.g.* increased risk of nitrogen leaching, nitrous oxide emissions (Vermeulen and Mosquera, 2009; Tim Chamen *et al.*, 2015) or increased risk of erosion (Braunack and Dexter, 1989; Bogunovic *et al.*, 2018). In addition to heavy loads, the intensity of traffic in the field is also a major cause to soil compaction problems (Arvidsson and Håkansson, 1991; Håkansson and Reeder, 1994; Keller *et al.*, 2004; Hamza and Anderson, 2005; Seehusen *et al.*, 2019). Traffic intensity is also in literature often referred to as wheeling intensity. Traffic intensity has been defined as the product of the weight of a machine and the distance driven per hectare (Arvidsson and Håkansson, 1991). Even if the first wheeling is considered most harmful (Bakker and Davis, 1995), repeated traffic causes additional stress and leads to accumulative plastic deformation (Bakker and Davis, 1995; Balbuena *et al.*, 2000; Horn, Way and Rostek, 2003; Schjønning *et al.*, 2016; Pulido-moncada, Munkholm and Schjønning, 2019). Repeated wheeling with lighter loads may even result in more harmful effects than a single heavy-loaded pass (Schjønning *et al.*, 2016; Seehusen *et al.*, 2019). The problems associated with soil and sub-soil compaction evidence the need for mitigation strategies caused by heavy and reiterative traffic in the field.

Various soil compaction mitigation strategies have been described in literature in regards to equipment, soil management, crops and field operations (Alakukku *et al.*, 2003; Chamen *et al.*, 2003; Keller and Arvidsson, 2004; Hamza and Anderson, 2005; Batey, 2009; Tim Chamen *et al.*, 2015). Equipment solutions to mitigate compaction are on-land ploughing (Munkholm, Schjønning and Rüegg, 2005), deep ripping (Schneider *et al.*, 2017), reduced wheel load by the use of tandem wheels, tandem axles and regulation of tyre inflation pressure (Keller and Arvidsson, 2004; Tim Chamen *et al.*, 2015). Soil management practices to limit soil compaction includes modelling soil readiness for assisting farm managers in scheduling when to operate in their fields (G. Edwards *et al.*, 2016; Obour, Keller, Jensen, *et al.*, 2019), and the use of well-designed drainage systems to reduce the water content and consequently increase the trafficability of the soil (Chamen *et al.*, 2003). Cover crops have also been found to be able to improve soil hydraulic properties and thereby reduce soil compaction problems (Çerçioğlu *et al.*, 2019). Finally, preventive field management practices can include controlled traffic farming (McHugh, Tullberg and Freebairn, 2009; Gasso *et al.*, 2013), or no-tillage (Renato Nunes *et al.*, 2018). In addition, reducing traffic intensity in heavy-loaded operations, such as harvesting, by the use of in-field optimised route planning (ORP) has been pointed out as a solution to reduce soil compaction problems (Bochtis, Sørensen and Green, 2012; Edwards *et al.*, 2017; Gorter, 2019). Bochtis et al. (2012) presented a decision support system (DSS) that used soil physical and chemical properties to estimate the potential risk of soil compaction and accordingly optimise the route of slurry application. The system was tested in one field and was able to reduce the risk factor by 61% compared to recorded data. Gorter (2019) presented an ORP method for capacitated harvesting operations that takes into account weight variations and soil compaction susceptibility based on infield wet areas. The method was tested in three fields and optimised the path of the grain cart according to its weight and the field areas more vulnerable to soil compaction. While the DSSs presented by Bochtis et al. (2012) and (Gorter, 2019) optimise in regards to soil compaction reduction and require field data collection prior to the operation to estimate the potential risk, the system employed in Edwards et al., (2017) reduced the travelled distance by the use of an ORP tool in neutral material flow operations, which reduced traffic intensity, especially in the headland area.

In this paper, a harvest logistics fleet optimisation tool, *i.e.* an ORP tool for harvesting operations (Villa-Henriksen *et al.*, 2018), was used to evaluate the effectiveness of ORP to reduce repeated traffic, heavy loads and accumulated traffic load, and thus the risk of soil compaction. The harvest fleet logistics system coordinate plans and optimises the route of all vehicles, so that the overall harvest time is minimised, as well as the travelled in-field distance is reduced. The ORP system does not require field data collection before the operation and addresses coupled operations with more than one vehicle carrying loads with varying weights, differing from Edwards et al., (2017) which only involves one vehicle with a constant weight.

It is hypothesised that ORP can reduce the in-field traffic, and consequently ORP can be employed as a complementary soil compaction mitigation strategy in arable farming.

4.2 Material and methods

An ORP tool for harvest operations (Villa-Henriksen *et al.*, 2018) was employed for optimising the operation in a set of recorded fields. The fields belonged to Lisbjerregård, a commercial farm located around Havndal in Jutland, Denmark (56.6530° N, 10.197475° E), which fields were harvested between the 8th and 14th of August of 2017. The position of all vehicles involved was recorded using GNSS loggers QSTARZ Travel Recorder XT, which use GPS satellites with a frequency of 1 Hz. In total six fields were fully recorded for the evaluation (Figure 16). The fields varied in size (2-21 ha) and shape and may be considered typical for Danish arable fields (Caspersen and Andersen, 2016; Enemark and Sørensen, 2016). Data from more fields were also recorded but had to be discarded because they either were incomplete or partially harvested at different times making them incomparable to the optimised solution.

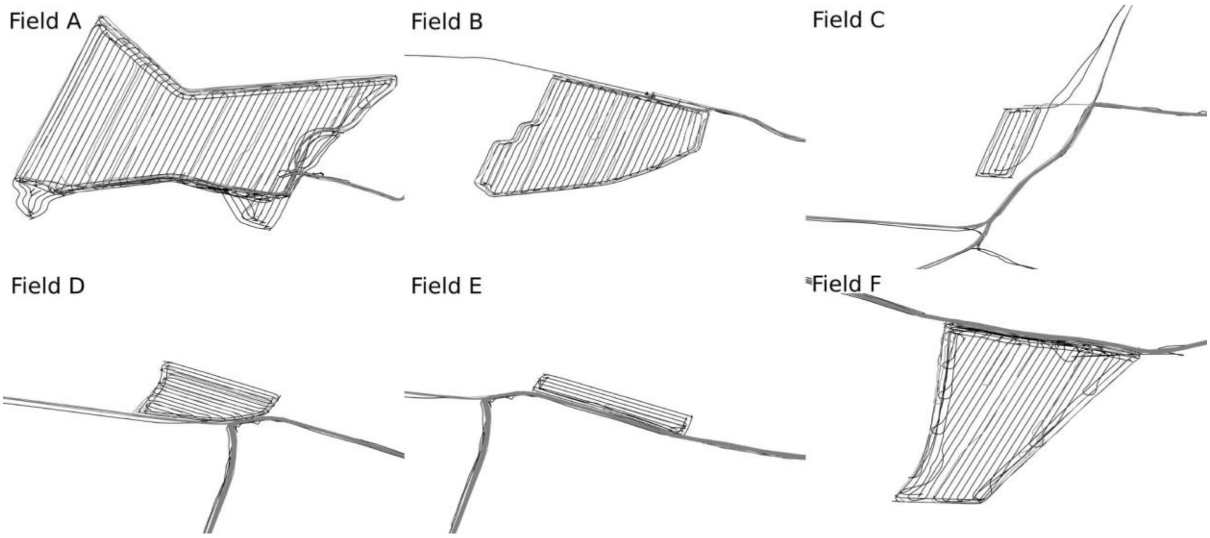

Figure 16. Raw position data of the recorded harvest operations used in the analysis.

The logged field harvest operations were analysed with the aim of having the same parameters in the computer optimised solution as in the recorded operations (Table 4). The total yield per field was calculated based on the CAN bus grain flow data from the harvester. The harvester was calibrated for a bulk density of the crop of 0.56 kg m^{-3}, which was used to estimate grain levels in harvester tank and grain carts. The vehicle speed parameters used in the simulations were 1.2 m s^{-1} for working speed, *i.e.* speed during harvesting, and 1.9 m s^{-1} for non-working speeds.

Table 4. Parameters used in the computer simulations for each of the fields

Field				Harvester			Grain cart	
Field ID	**Size (ha)**	**No. headlands**	**Total crop output (Mg)**	**Working width (m)**	**Harvester Tank volume (m^3)**	**No. trailers**	**Volume (m^3)**	**Time out of field (s)**
A	21	3	82.54	12	14.5	1	31	1367
B	9.4	2	39.14	12	14.5	1	26	1025
C	1.6	2	6.61	12	14.5	1	26	0
D	3.1	2	10.72	12	14.5	1	26	0
E	2	2	6.02	12	14.5	1	26	0
F	12.7	3	51.65	12	14.5	1	26	931

The ORP tool employed for the harvest operations coordinate plans and optimises the route of harvester and grain carts, so that the overall harvest time is optimised, as well as the travelled distance is minimised. The system ensures the grain carts will receive the loads at the right time and at the right spot. The harvesting of the set of fields was computer simulated with the input parameters registered (Table 4). The harvester weight was 28982 kg. and the grain cart weight including the tractor was 16320 kg. The app-based version of the ORP fleet harvest tool has been described in Villa-Henriksen *et al.* (2018).

The position data for the recorded operations was processed before the evaluation analysis by removing all data points placed outside of the field polygon boundaries as well as points outside of the time range in which the fields were harvested. It was observed during the analysis that Field A lacked data points from the grain cart due to issues in the setup of the GPS logger. In order to calculate the traffic of Field A, the missing position data were estimated by interpolation adding one data point per missing timestamp in a straight line within the existing adjacent data points.

For the evaluation, the fields were divided into a grid where the gridline spacing was equal to the working width of the harvester, *i.e.* 12 metres, and the orientation of the grid followed the angle of the working direction in the main part of the field. For each of the grid cells three variables were measured, *i.e.* traffic occurrences, accumulated traffic load per grid cell and maximum traffic load per grid cell. Traffic occurrences refers to the number of times any vehicle has driven on a grid cell and accounts for repeated traffic. Accumulated traffic load per grid cell represents the sum of the weights of vehicles passing the grid cell including the harvested grain in their tank or grain cart. Finally, the maximum traffic load per grid cell expressed the heaviest vehicle including grain content that has passed over the grid cell. This last variable was analysed in order to address the possible effects on load from using ORP. The traffic occurrences distributed across field grid cells were displayed in map form and in bar chart of the percentage of trafficked grid cells.

For each of the fields the total sum, the mean and standard deviations, the median, as well as the maximum values for each of the three variables were calculated. Additionally, the relative difference (Eq. 1) for each field and variable was also calculated, *i.e.* the difference between recorded (x_r) and simulated (x_s) total traffic occurrences per field divided by the arithmetic mean.

$$Relative\ difference\ (x_r, x_s) = \frac{x_r - x_s}{\bar{x}} \qquad \text{Eq.1}$$

Finally, the field size weighted arithmetic mean of the relative differences for each of the variables were calculated. The field size was based on the number of grid cells attributed to each field.

The harvesting times for the ORP tool and recorded operations are not included in this study because they do not affect the traffic variables studied and would require a thorough analysis of recorded speeds and accelerations as well as to include them cautiously in the simulation to achieve an equitable comparison, which is not in the scope of the article.

The correlation between the accumulated traffic load and traffic occurrences was also studied to observe its dependency in order to address the possibility of estimating accumulated weight based only on traffic occurrences. The correlation analysis was divided into the two different grain cart volumes employed in the harvest operations, *i.e.* 31 m^{-3} used in Field A, and 26 m^{-3} in the rest of fields (Table 4).

The processing and analysis were performed using targeted code in Java and Python programming languages and the spatial data was visualised employing QGIS v. 2.14.

4.3 Results

The harvest logistics tool reduced the total number of traffic occurrences per grid cell in the set of fields with a field size weighted mean of the relative differences of 9.8%, or 12.9% when Field F is excluded. The relative difference of total traffic occurrences ranged from 0.7% to 50.5%. The median of the simulated harvest was reduced from 2 to 1 traffic occurrence per grid cell in all fields, excluding Field E and F where it was equal. The results for maximum traffic load per grid cell were higher for all fields for the ORP tool with a field size weighted mean of relative differences of -4.0%, and the relative differences ranging from -1.9% to -5.1%. The results for the ORP tool for the accumulated traffic load per grid cell were reduced in 5 of the fields and increased in one of them, having a field size weighted mean of relative differences of 5.6%, and the relative difference ranging from -4.3% to 39.8%. The medians of the accumulated weight per grid cell was importantly reduced in Fields A, B, C and D, while for Fields E and F was slightly higher. The complete results for traffic occurrences (Table 5), maximum traffic load per grid cell (Table 6) and accumulated traffic load (Table 7) are collected each in a dedicated table. A bar chart for each field with the distribution of traffic occurrences for the recorded and simulated data is shown in Figure 18. In the figure, it is observed that the simulated data tends to be more positively skewed than the recorded data, meaning that there were more grid cells being travelled on one or two times and less with higher traffic occurrences. The percentage of grid cells with more than one traffic occurrence was reduced in all but two fields, *i.e.* Field E and Field F. The field traffic maps for recorded and simulated data are presented in Figure 17, where it is visualised in colour-scale the lighter and heavier trafficked areas.

Table 5. Traffic occurrences

Field			**Recorded**				**Simulated**				**Relative difference**
ID	**Area (ha)**	**Grid cells**	**Total**	**Mean per grid cell (SD)**	**Median**	**Max**	**Total**	**Mean per grid cell (SD)**	**Median**	**Max**	**(%)**
A	21	1501	3533	2.4 (2.2)	2	16	3182	2.2 (1.6)	1	16	10.5
B	9.4	685	1381	2.1 (1.3)	2	9	1321	2.0 (1.4)	1	9	4.4
C	1.6	115	263	2.3 (1.0)	2	6	157	1.4 (1.0)	1	6	50.5
D	3.1	227	551	2.4 (1.5)	2	8	358	1.6 (1.1)	1	8	42.5
E	2	152	245	1.6 (1.1)	1	7	240	1.6 (0.9)	1	8	2.1
F	12.7	879	1785	2.0 (1.4)	2	9	1774	2.0 (1.3)	2	10	0.7
Field size weighted arithmetic mean											**9.8**

Table 6. Maximum traffic load (Mg)												
Field			**Recorded**				**Simulated**				**Relative difference**	
ID	**Area (ha)**	**Grid cells**	**Total**	**Mean per grid cell (SD)**	**Median**	**Max**	**Total**	**Mean per grid cell (SD)**	**Median**	**Max**	**(%)**
A	21	1501	47432.3	31.6 (2.1)	31.7	36.4	49617.4	33.5 (2.2)	33.8	37.2	-4.5
B	9.4	685	21653.5	32.2 (2.2)	31.8	36.8	22124.9	33.0 (2.1)	32.9	37.1	-2.2
C	1.6	115	3488.1	30.3 (0.9)	30.5	31.9	3663.1	32.4 (1.9)	32.5	35.4	-4.9
D	3.1	227	7065.1	31.1 (2.7)	31.6	34.1	7324.9	32.4 (2.3)	31.8	36.9	-3.6
E	2	152	4800.3	32.0 (3.0)	32.4	35.0	4893.9	32.2 (1.8)	32.2	35.2	-1.9
F	12.7	879	27677.7	31.5 (2.4)	31.7	35.7	29116.7	33.4 (2.1)	33.4	37.2	-5.1
Field size weighted arithmetic mean											**-4.0**

Table 7. Accumulated traffic load (Mg)											
Field			**Recorded**				**Simulated**				**Relative difference**
ID	**Area (ha)**	**Grid cells**	**Total**	**Mean per grid cell (SD)**	**Median**	**Max**	**Total**	**Mean per grid cell (SD)**	**Median**	**Max**	**(%)**
A	21	1501	101516.1	67.6 (60.9)	48.2	431.8	95406.1	64.3 (45.3)	36.9	430.6	6.2
B	9.4	685	40723.3	60.6 (38.5)	53.3	254.5	40098.4	59.8 (40.4)	36.3	254.8	1.6
C	1.6	115	7056.6	61.4 (27.3)	53.1	172.4	4715.2	41.7 (24.2)	33.0	165.7	39.8
D	3.1	227	15265.8	67.3 (39.5)	57.5	229.8	10938.7	48.4 (31.2)	35.0	228.0	33.0
E	2	152	7592.0	50.6 (33.5)	33.9	185.5	7017.6	46.2 (24.3)	34.7	224.5	7.9
F	12.7	879	50734.5	57.7 (36.5)	47.6	261.3	52967.1	60.7 (35.1)	52.7	252.1	-4.3
Field size weighted arithmetic mean											**5.6**

The results indicate a high correlation between the accumulated traffic load and traffic occurrences for both grain cart volumes employed in the harvest (Figure 19). The coefficient of determination (R^2) for the bigger grain cart was 0.994 for the recorded field and 0.988 for the simulated field. The coefficient of determination for the smaller grain cart 0.983 for the recorded fields and 0.986 for the simulated fields.

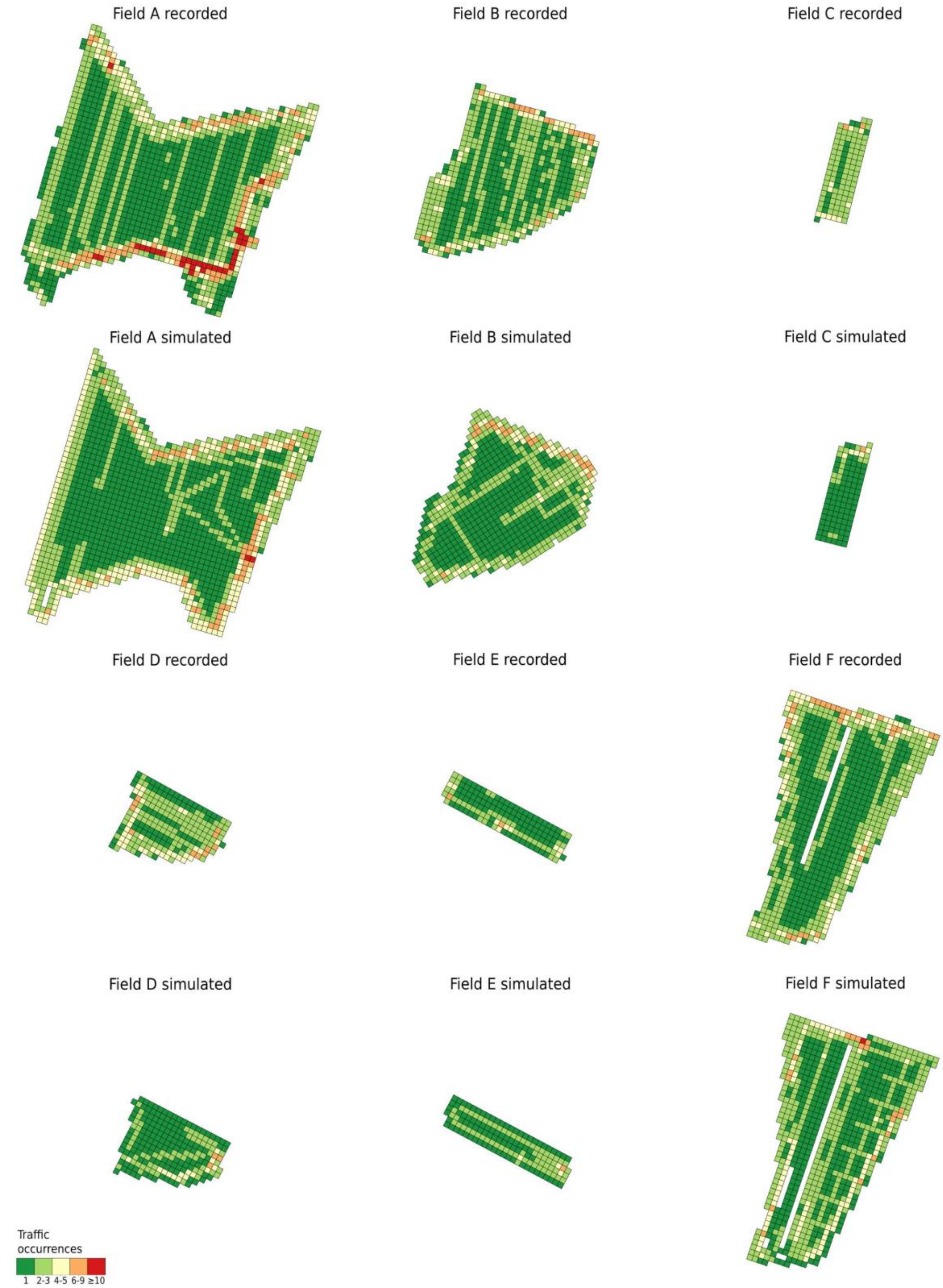

Figure 17. Traffic occurrence maps of the fields studied for the recorded and simulated harvest operations.

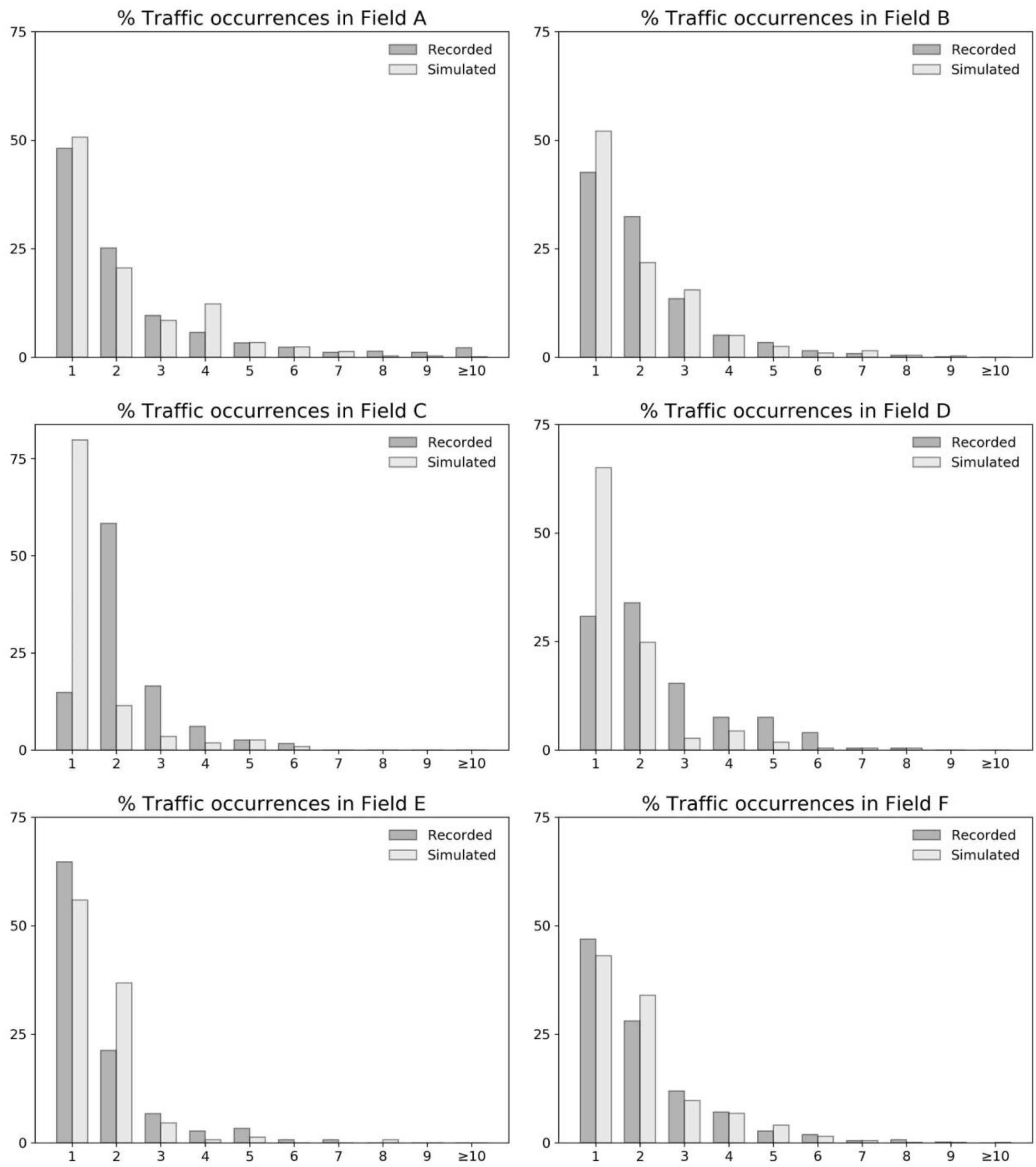

Figure 18. Bar charts of the set of fields comparing the distribution in percentage of the traffic occurrences for the recorded and simulated harvest operations.

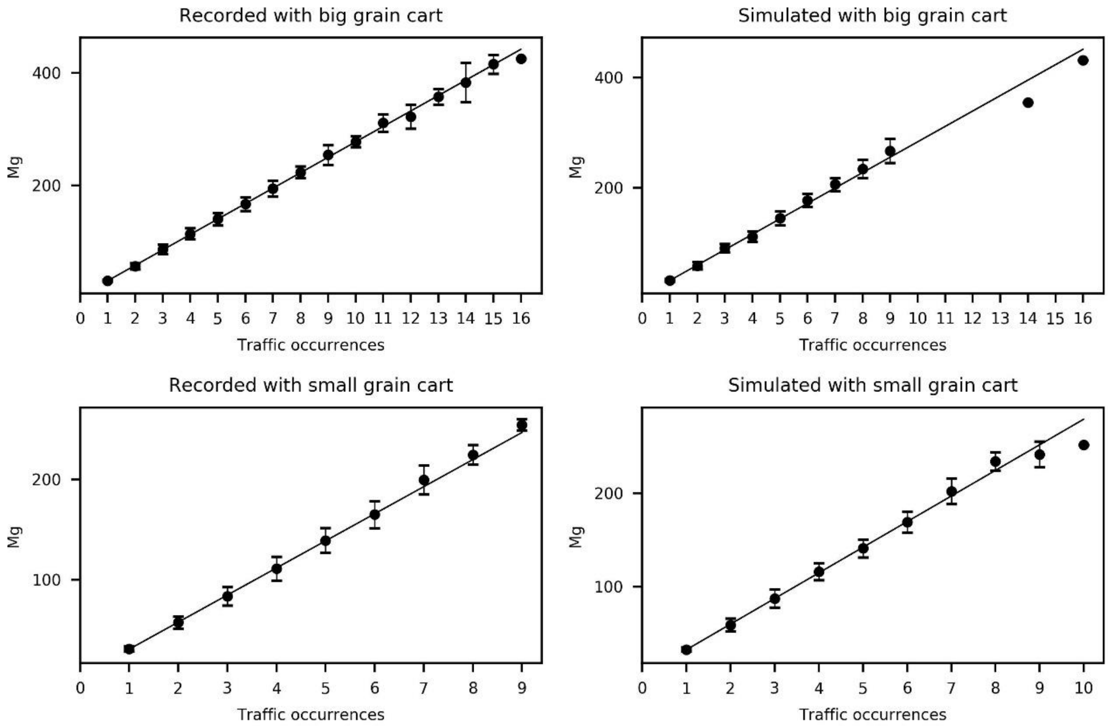

Figure 19. Correlation between accumulated traffic load and traffic occurrences for the two sizes of grain carts employed.

4.4 Discussion

4.4.1 Repeated traffic

The ORP tool for harvest logistics was able to provide an optimised solution for the whole set of fields recorded, which were of different shapes and areas ranging from 1.6 to 21 hectares. One of the fields, *i.e.* Field F, included an obstacle in the middle of the main working area. The ORP tool aims to reduce the overall operational time of a harvest operation and reduce as well the travelled distance in the field as a second goal. This means that in certain cases, the harvester may travel a longer distance, *e.g.* when the model predicts that a grain cart is delayed to receive a load it makes the harvester leap over adjacent rows and harvest closer to the gate so that the overall operational time is reduced. However, as the tool coordinates all vehicles involved in the operation so that the grain carts are always directed to an unloading point at the right time and location, it reduces in that manner unnecessary infield traffic. Consequently, even though the model is not intended for reducing the in-field traffic, the optimised solution reduced the traffic occurrences in all fields with a field size weighted mean of the relative differences of 9.8% (Table 5). Nevertheless, in field F, the relative difference was neglectable, *i.e.* 0.7%. Field F was also the only case where the ORP tool could not obtain a median value per grid cell below 2 traffic occurrences. This field performed also worse for the optimised solution in regards to accumulated traffic load compared to the rest of fields where the simulation reduced the accumulated weight. In Field F (Figure 17), as the ORP tool optimises the overall harvest time, the optimised solution provided two different driving directions separated by the elongated obstacle in the middle of the field. One of the directions was parallel to the obstacle while the other was not, meaning additional turns by its side and consequently more traffic occurrences. The ORP tool would require some intrinsic changes in the optimisation algorithms to truly aim for in-field traffic reduction in any type of field. If field F is excluded, the traffic occurrences would be reduced by a field size weighted mean of the relative differences of 12.9% when employing the ORP tool.

The ORP tool performed particularly well in Field C and Field D (Table 5 and Figure 18), which had very small field areas, with relative differences of 50.5% and 42.5% respectively. In these fields, as well as in Field E, the total yield output was smaller than the grain cart size, implying that the harvester had to empty its grain tank two times at most (Table 4). The recorded data shows that the grain carts travelled unnecessary distances as they did not know how to drive strategically in the field to meet the harvester at the right time and place, resulting in additional traffic. In the simulated operation, the grain carts minimised their traffic by waiting by the gate until they timely drove to receive an unload. This characteristic of the ORP tool reduces significantly the traffic occurrences produced by the grain carts, and in general the overall in-field traffic in harvest operations. Considering that the harvester has to traverse the whole field, *i.e.* at least one time per grid cell, a field size weighted mean of relative differences of 9.8% is an important reduction, especially taking into consideration the median values for the simulated data (Table 5), in which four of them were reduced from 2 to 1 traffic occurrences per grid cell.

The percentage of grid cells with repeated traffic, *i.e.* with more than one traffic occurrence, is important for evaluating the effectiveness of an ORP tool to reduce repeated traffic. The simulated harvest was able to reduce repeated traffic in four of the six fields (Figure 18). The reduction was especially important in Field C and D and did not occur for Field E and F. In the recorded data, all the fields excluding Field E had repeated traffic in more than 50% of the grid cells, meaning that more than half of the field surface is prone to experience the negative consequences of repeated traffic. Any reduction in the percentage of grid cells with repeated traffic will avoid its negative effects in those parts of the field. The simulated data had repeated traffic in less than 50% of the grid cells in five of the six fields. Even though Fields E and F had overall traffic reduced (Table 5), they had more repeated traffic than the recorded data (Figure 18). In Field F this was caused by the orientation of the rows in relation to the obstacle in the middle of the field, as previously discussed. In Field E it was caused by the optimisation calculating an unloading point at the opposite edge of the field in regards to the gate, obliging the grain cart to drive a longer path than in the recorded data. As the ORP tool aims at reducing the overall operational time, this issue may occur in some smaller fields with one in-field unload.

In the set of fields studied, field size does not have a relation to repeated traffic reduction, as the unpredictable human factor has very much influence on the traffic in the recorded fields. With a larger dataset it would be expected to have in average a higher reduction for larger fields, than for smaller. This is mainly because the ORP tool reduces ineffective travelled distances by the grain carts and the number of unloads is minimised, thus having more effect in the reduction of repeated traffic. Field shape may also influence the reduction of repeated traffic as more complex fields can become more challenging for the operators to drive optimally, so the ORP tool could potentially be more effective. However, in some cases the ORP tool may optimise harvest time reduction in a way that does not benefit traffic reduction, *e.g.* in the case of Field F. Larger datasets would be required to analyse the relation between traffic and field size and shape, as well as the capability of an ORP tool to reduce traffic in any type of field.

The results indicate a high correlation between the accumulated traffic load and traffic occurrences (Figure 19). The coefficient of determination (R^2) for the bigger and smaller grain carts and for both recorded and simulated harvesting operations rounded 0.99, which shows a very high correlation. Consequently, in this specific case, it also indicates that traffic occurrences do not require weight as a parameter in the calculations in order to predict the traffic occurrences. The cause for this correlation is twofold: the high weight of the harvester, which has to drive over each grid cell of the field, and the relatively small weight differences between full (8 Mg) or empty tanks in regards to the harvester weight (29 Mg). Additionally, as the tractor with a full grain cart sums around 34 Mg, which is very close to the harvester weight with a full load, the relation to traffic occurrences becomes apparent.

4.4.2 Heavy loads

Heavy load leads to subsoil compaction (Håkansson, Voorhees and Riley, 1988; Keller *et al.*, 2019). Consequently, the maximum traffic load per grid cell was included in this study. The results show that the maximum traffic load per grid cell was higher for the ORP than for the recorded data, mainly because the ORP model filled the grain cart always to 100%, which was not the case in the recorded data. The results show a field size weighted mean of relative differences of -4.0% for the maximum traffic load per grid cell. This could be caused by yield sensor calibration issues or because the operators had to guess on the go when a tank or grain cart was really full. Nonetheless, looking closer to the results, the maximum traffic load per grid cell had mean values around 30-33 Mg with standard deviations of 1-3 Mg (Table 6), and the differences between average recorded and simulated data were in fact in all cases smaller than 2 Mg per vehicle. This suggests that for a given fleet of vehicles for grain harvest, ORP does not significantly increase the risk of soil compaction due to heavy traffic load but significantly reduces repeated traffic as previously stated.

The concept of traffic intensity described by Arvidsson & Håkansson (1991) refers to the product of the weight of a machine and the driven distance per hectare (Mg km ha^{-1}), which includes heavy loads and in-field travelled distance in one variable, and can cover a whole season of field operations. The in-field travelled distance is related to the repeated traffic. The concept of traffic intensity was employed by Gorter (2019) for estimating the reduction of travelled distances by heavy loaded machinery in wet areas. In this study, a different approach was chosen, which distinguishes heavy loads from repeated traffic, and has a much finer spatial resolution than a hectare, *i.e.* squares of 12 meters sides.

Nonetheless, the method used to calculate traffic occurrences and load may not provide the full picture, as the weight is not equally distributed inside the grid cell. Furthermore, equal traffic loads per grid cell for different vehicles can translate into very different induced stress on the soil. The weight distribution is dependent on the axel load for each wheel along with the contact area of the wheel (Keller and Arvidsson, 2004; Hamza and Anderson, 2005; Seehusen *et al.*, 2019). The axel load is subjected to mechanical design of the vehicle, which can distribute the weight differently between for example front and back wheels. The contact area is dependent on the inflation pressure and the tyre design. Due to most of these parameters were not known during the harvest operations, the focus has been set on traffic occurrences per grid cell, knowing that repeated traffic can be more harmful to soil structure than single wheeling with high load (Seehusen *et al.*, 2019). Modelling tools such as Terranimo (Stettler *et al.*, 2014), FRIDA (Schjønning *et al.*, 2008) as well as other scientific models (*e.g.* Thomas Keller & Arvidsson, 2016) can be employed to simulate and study the wheel stress induced to the soil and the compaction for different soil types and conditions.

4.4.3 Accumulated traffic

Even if the first wheeling is considered most harmful, repeated traffic results in accumulated plastic soil deformation and compaction (Bakker and Davis, 1995; Horn, Way and Rostek, 2003; Seehusen *et al.*, 2019), with significant yield penalties compared to single-pass traffic (Arvidsson and Håkansson, 1991; Schjønning *et al.*, 2016), and may lead to subsoil compaction with long term persistence (Håkansson, Voorhees and Riley, 1988; Balbuena *et al.*, 2000; Pulido-moncada, Munkholm and Schjønning, 2019). As in harvesting operations the first wheeling is unavoidable, since the harvester needs to harvest the whole field, the reduction of additional traffic is central in these types of operations. This is particularly relevant when the soil conditions are not ideal. Considering the constrained time frames operators are forced to work on due to weather conditions or farm scheduling limitations, it obliges them to drive under suboptimal soil conditions increasing soil compaction issues (Orfanou *et al.*, 2013; Edwards, 2015; G. Edwards *et al.*, 2016).

The negative effects of accumulated traffic in soil compaction are not only dependent on the soil conditions, but as discussed earlier, also on the weight distribution and wheel contact area of the different vehicles, which were unknown in this study. Additionally, the differences in axle width, wheel number and distribution, as well as the driving patterns inside a grid cell of the harvester and grain carts make the negative effects in soil compaction of accumulated traffic difficult to estimate.

The accumulated traffic load per grid cell was reduced in most of the fields studied resulting in a field size weighted mean of relative differences of 5.6% (Table 7). As described previously, the accumulated load per grid cell is directly correlated to the traffic occurrences, which makes the count of traffic occurrences a straightforward concept to account for repeated traffic and could potentially be used for estimating the approximate effects of accumulated traffic load in localised areas.

From the traffic maps (Figure 17) it is clear that the grain carts in the simulated data drove across the field making the shortest connection from or to an unloading event. This happens also sometimes in real life but may not be the ideal situation since the driving direction is not respected in the main field area, and is unacceptable in controlled traffic farming.

4.4.4 Applicability of the ORP tool

Soil compaction induced by vehicle traffic may not be possible to eliminate entirely, but it can be reduced by employing intelligent tools that can manage vehicle traffic (Raper, 2005). ORP besides optimising the operation in time (Bochtis, Sørensen and Green, 2012; Bochtis, Sørensen and Busato, 2014; Edwards *et al.*, 2017), it does also reduce vehicle traffic in the set of fields studied in this paper. ORP can be therefore considered a soil mitigation strategy that in combination with other strategies can reduce the degradation of arable soils across the globe. ORP does not require major investments or changes in the machinery fleet of the farm, as it can be without difficulty employed through smart technologies (Villa-Henriksen *et al.*, 2018).

In order to minimise further soil compaction, ORP for capacitated operations can be targeted include the wheel load carrying capacity of the soil in a field in the route planning. In that manner, the vehicles are directed to avoid the wettest areas of a field when carrying heavy loads. ORP that targets minimising risk for soil compaction have been proposed for slurry application (Bochtis, Sørensen and Green, 2012) as well as for root crop harvesting operations (Gorter, 2019). The ORP tool employed in this study does not require any data collection prior to the operation and can reduce the traffic occurrences in the field, but does not consider high risk areas, which may cause soil compaction problems. Bochtis et al., (2012) altered the driving direction of the operation according to an electrical conductivity map of the field that addressed the risk of soil compaction. The map was generated from field measurements prior to the operation and based on it the ORP system directed the tractor in accordance to its load and the soil risk factor. Gorter (2019) aimed to reduce the distance of heavy loaded grain carts in fictive wet areas for high yielding root crops based on a capacitated arc routing problem with a Tabu search algorithm. ORP with special attention to soil compaction risk requires previous mapping based on either in-field measurements or on modelling tools. In that manner, ORP can significantly reduce soil compaction across the field in general, and specifically in high risk areas. However, altering the route according to a wheel load carrying capacity map may imply more repeated traffic in certain areas and more distance travelled by the vehicles. Further research should address these issues, optimising the operation in time but altering the route according to a carrying capacity map and the load of the vehicles.

4.5 Conclusion

A harvest logistics fleet optimisation system was employed to simulate traffic occurrences for a set of fields as well as compared it to the non-optimised recorded harvest traffic occurrences The results show that the ORP tool was able to reduce traffic occurrences with a field size weighted mean of relative differences of 9.8% and reducing repeated traffic in four of the six fields studied. The tool performed better in some fields than others, but for all cases, the tool managed to decrease he traffic occurrences. As the tool coordinates the vehicles for timely unloading events, it avoids unnecessary traffic from especially the grain carts, consequently reducing the total traffic in the field. Even though ORP is not directly intended for in-field traffic reduction, it can accomplish this task and adds an extra element to the farm strategy for reducing soil compaction. It can be concluded that soil compaction resulting from vehicle traffic can potentially be reduced by the use of optimised route planning, especially when soil conditions are not ideal.

Chapter 5 Evaluation of grain quality-based simulated selective harvest performed by an autonomous agricultural robot

Andrés Villa-Henriksen[a,b], Gareth T.C. Edwards[b], Ole Green[b,c], Claus A.G. Sørensen[a]

[a] *Aarhus University, Department of Electrical and Computer Engineering*

[b] *Agro Intelligence ApS*

[c] *Aarhus University, Department of Agroecology*

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Abstract

Grain price differences due to protein content can have economic effects on the farm as well as environmental effects when alternative protein sources are imported. Grain protein variability can vary from year to year due to environmental factors and can be addressed by site-specific management practices. Alternatively, it can be addressed at harvest time by selective harvest. Agricultural autonomous robots can accurately follow alternative harvesting routes that are subject to grain quality maps, making them suitable choices for selective harvest. This study addresses therefore the potential revenue of selective harvest performed by the route planner of an autonomous field robot. The harvest capacity and potential economic revenues of selective harvest in a Danish context were studied for a set of 20 winter wheat fields with 4 hypothetical scenarios. The results showed significant differences in harvest capacity between conventional and selective harvest. Even though in some scenarios selective harvest did not require notable additional harvest times, the cost-benefit analysis showed small economic returns of up to 46 DKK ha^{-1} for the best scenarios, and for most cases losses up to 464 DKK ha^{-1}. Additionally, the location of the high protein content areas has great influence on the profitability of selective harvest.

5.1 Introduction

Grain prices depend on their protein content and have economic consequences as farmers are forced to increase the import of protein sources to fodder or obtain lower prices for their grain crops due to different end-use functionalities, e.g. flour milling contrasted with starch manufacturing (Farquharson, 2006; Punia, Singh and Kumar, 2019; Styczen *et al.*, 2020). The import of alternative protein sources, e.g. soybeans (*Glycine max* L.), is not only expensive for the farmer, it has also important environmental consequences, such biodiversity losses (Richards *et al.*, 2012) or increased emissions of greenhouse gasses (Pelletier, 2008). Even though nitrogen fertilisation and cultivars have a direct effect on the protein content of the grain (Farquharson, 2006; Havlin and Heiniger, 2009; Punia, Singh and Kumar, 2019), the harvest year and other environmental factors can have even a higher influence (Basso *et al.*, 2009; Fronzek *et al.*, 2018; Pronin *et al.*, 2020; Styczen *et al.*, 2020). These factors do not only affect the overall crop quality in a field, but can also create important variations within the field (Godwin and Miller, 2003; Guerrero, Neve and Mouazen, 2021). Besides protein content, other variables can also define the quality of the grain, which have an influence on its final use as well as price, e.g. mycotoxin infections (Whetton, Waine and Mouazen, 2018) or grain moisture (Czechlowski and Wojciechowski, 2013; Punia, Singh and Kumar, 2019).

Since the Global Positioning System (GPS) technology was made globally available without deliberate quality degrading, conventional agriculture started to move into precision agriculture where in-field variability can be addressed by variable rate applications as well as other site-specific management practices (Christensen *et al.*, 2009; Peets *et al.*, 2012; Guerrero, Neve and Mouazen, 2021). These site-specific management techniques aim to improve the grain quality and quantity, and make the use of resources more efficient, which improve the economic return of the farm (Havlin and Heiniger, 2009).

Alternatively, infield grain variability has also been proposed to be addressed at harvesting time through selective harvest (SH), where grain is harvested separately according to its predetermined quality, e.g. protein content. Separating grain by quality during harvest can be employed to capture grain price premiums, as some markets categorise some grains into grain quality groups (Meyer-Aurich *et al.*, 2008; Long, Mccallum and Scharf, 2013; Martin, Mccallum and Long, 2013; Risius *et al.*, 2015). The cost-benefits of SH have specifically been studied by the grain price differences of wheat based on protein content (Tozer and Isbister, 2007; Meyer-Aurich *et al.*, 2008; Martin, Mccallum and Long, 2013) as well as mycotoxin infections (Whetton, Waine and Mouazen, 2018), concluding that there is potentially measurable total profits to be gained for SH. (Whetton, Waine and Mouazen, 2018) found potential gross profits of 48 GBP ha^{-1} for SH in regard to wheat mycotoxin infection. (Martin, Mccallum and Long, 2013) found that segregating wheat grain between 12% to 14% in protein content can provide a marginal returns between 2.94 USD Mg^{-1} to 5.51 USD Mg^{-1} respectively. (Meyer-Aurich *et* *al.*, 2008) found potential profits of more than 32 EUR ha^{-1} in some cases of SH of wheat. While (Tozer and Isbister, 2007) found that dividing the fields in management zones that were harvested selectively gave losses in some scenarios while in others extra revenues of e.g. 9.53 AUD ha^{-1}.

Different SH strategies have been presented in the scientific literature. One of the strategies consists in separating the grain stream into two bins in the combine during the harvest. This can be achieved by either real-time measurements (Risius, Hahn and Korte, 2010; Long, Mccallum and Scharf, 2013), or by predicting the grain quality based on the locally variable environmental conditions (Czechlowski and Wojciechowski, 2013; Niedbała, Czechlowski and Wojciechowski, 2013), or by a combination of modelling and monitoring (Wojciechowski *et al.*, 2016). A simpler approach can be accomplished by actively monitoring the grain flow to redirect and optimise the processing and marketing of the harvested batches independently (Bonfil *et al.*, 2008; Risius *et al.*, 2015). Finally, a different strategy is to divide the field into management zones, which are then harvested selectively (Tozer and Isbister, 2007; Meyer-Aurich *et al.*, 2008; Whetton, Waine and Mouazen, 2018). Each of these SH strategies present different challenges, e.g. reduced grain tank capacity when two bins are implemented in the combine harvester, too high variations in the values generated by sensors that increases the difficulty of segregating the grain stream by a diverter valve in a combine with two bins, or the reduced scalability of the grain quality predictive models. Regarding SH by management zones, the different approaches found in literature do not cover the practical aspects of harvesting selectively, as they estimate the extra harvesting costs by the harvesting distances to be covered but do not consider the additional distances of the connection paths and turning areas, or the practical issues of how the harvester operator can distinguish the different management zones from each other in order to harvest selectively.

Thanks to the Internet of Things (IoT) applied to agriculture, robotics and autonomous vehicles can perform in the near future the same field operations that currently rely on traditional human-agricultural vehicles interactions (Kayacan *et al.*, 2015; Bechar and Vigneault, 2016; Ren and Martynenko, 2018; Moysiadis *et al.*, 2020; Villa-Henriksen, Edwards, *et al.*, 2020; Araújo *et al.*, 2021). Furthermore, autonomous agricultural robots can operate in fields accurately following site-specific and optimised route plans that are presently challenging for human operators with the newest machinery, even if assisted by smart navigation devices (e.g. (Villa-Henriksen *et al.*, 2018)). Optimised route planning has been successfully implemented in harvesting operations with the advantage of improving the harvest capacity of the vehicles and saving operational time (Busato, Berruto and Saunders, 2007; Jensen *et al.*, 2012; Edwards *et al.*, 2015b, 2017; Seyyedhasani and Dvorak, 2017), which as a result reduces the risk of soil compaction (Villa-Henriksen, Edwards, *et al.*, 2020). In addition, optimised route planning can also be used to redirect the routes according to infield spatial variations (Bochtis, Sørensen and Green, 2012; Gorter, 2019). Therefore, autonomous agricultural robots and optimised route planning have great potential to be employed in SH. Agricultural vehicle robots have the advantage of following accurately a specific SH route that is different from the conventional harvest route and that can not necessarily be visible in the field to the human eye. In addition, the recent technological advances in monitoring, remote sensing and modelling are allowing rapid non-invasive methods to reliably map the grain quality of a field prior harvesting (Godwin and Miller, 2003; Joshi *et al.*, 2016). In order to avoid the challenges of segregating the grain into two bins while harvesting a new approach is studied in this manuscript, where the route plan of a robotic harvester is determined by a grain quality map so that the different qualities are harvested separately at different times. Similar to the management zones presented by (Whetton, Waine and Mouazen, 2018) and by (Tozer and Isbister, 2007) the SH strategy studied in this paper relies on reliable grain quality maps that may be generated by machine learning as well as scientific models or by remote sensed measurements (e.g. (Palosuo *et al.*, 2011; Leroux and Tisseyre, 2018; Gyldengren *et al.*, 2020; Styczen *et al.*, 2020)). However, (Whetton, Waine and Mouazen, 2018) do not describe how harvesting the different management zones would take place, as the study focuses mainly on the management zone creation and the cost-benefit analysis of SH and variable-rate applications. And neither does (Tozer and Isbister, 2007) address the practical issues of route planning in the SH proposed in their study, even though they do take into consideration diverse driving directions and the subsequent extra distances to drive during harvest in their calculations.

SH can address some of the sustainability issues associated with the suboptimal conventional harvest, which consider the whole field uniformly. Grain quality indicators such as mycotoxin concentration, moisture content or protein content directly affect its processing and possible end-usage, which can imply grain downgrading (Parry, Jenkinson and McLeod, 1995), food contamination (Paul, Lipps and Madden, 2005) and ultimately food waste even if some parts of the grain are recognised high-quality (FAO, 2011) with subsequent social, environmental and economic consequences.

This study addresses the potential revenue of harvesting separately higher grain quality areas from the remaining part of the field by the use of an autonomous field robot. Autonomous agricultural robots have the advantage of reliably following a route plan that addresses the quality areas in a field that are not necessarily visible by the human eye. Additionally, this study takes into consideration the full implications of the route alterations of SH in specific designed cases. It is hypothesised that selective harvesting based on assessed infield protein content variability is economically feasible in a Danish farming context. Consequently, the aim of this study was to (a) determine the harvest capacity of SH in different scenarios against conventional harvest; and (b) examine the potential economic benefits of harvesting selectively winter wheat in a Danish context. To achieve this, a set of fields with hypothetical grain quality scenarios were studied by the use of route planning simulations for an autonomous agricultural robot.

5.2 Materials and methods

5.2.1 Route planning with autonomous field robot

The simulated task times are based on the route planner of the autonomous agricultural robot Robotti, which was first described in (Green *et al.*, 2014), and later mentioned in (Foldager *et al.*, 2018). An up-to-date description of Robotti can be found in its homepage (AgroIntelli, 2021). Robotti is designed to carry and operate a varied range of implements, but can currently not perform grain harvest operations. Nonetheless, the route planner that directs the robot across the field can make plans that can be employed for harvest operations, where the headlands are harvested first and the main field area thereafter. In order to perform selective harvest, it is assumed that the areas with high quality grain are smaller than the rest of the field with lower quality. The field is then harvested considering the high-quality (HQ) areas as subfields or obstacles to avoid when harvesting the lower quality crop. Once this part of the field is fully harvested, the high-quality areas are then harvested and the grain is loaded on trailers to be stored independently from the rest of the harvested grain. For the simulations the autonomous harvester robot is assisted by two grain carts with 10 Mg of capacity each.

To assess this future scenario some assumptions are required to make the analysis comparable: (a) the storage capacities are equally distanced from the harvested fields and are close enough, so that two grain carts are sufficient to assist the robot harvester without waiting times; and (b) there is a uniform yield distribution across the fields.

The route planner method used in this study intentionally follows a row-by-row approach which emulates conventional harvest and reduces the potential influence of the heuristic optimisation method employed. The Tabu search algorithm of the route planner optimises the connections between rows and work areas. The estimated total operational times by the route planner are based on a set of inputs. They also include the vehicle kinematics in the calculations, i.e. accelerations and decelerations, as well as the steering dynamics. The route planner also takes into account the driving time from the harvesting end-point to the gate. The robot harvester inputs have been chosen based on the current maximum working width of Robotti, i.e. 3 metres, and operational speeds of 1.39 m s^{-1} that are both reachable by Robotti and by modern harvesters from a conservative point of view. As the crop yield has been assumed uniform across the fields, the threshing capacity will not be altered, and therefore, the working speed can be kept constant. Additionally, it is needed to be mentioned that Robotti can perform “zero turn” manoeuvres, i.e. spin about a stationary point, and the plans include this manoeuvre in the paths for connecting rows.

5.2.2 Set of fields selection

A set of fields was generated from the latest national list of agricultural fields from the Danish Agricultural Agency (LBST) from the Ministry of Food, Agriculture and fisheries of Denmark (LBST, 2021). A few steps were required to create the set of fields for this study: (a) from the original dataset from 2019, all the fields where cereals had been cultivated were selected; (b) all fields with registered obstacles inside the field were excluded; (c) based on the field complexity geometric feature found in Skou-Nielsen, Villa-Henriksen, Green, & Edwards, (2017), the 25% most complicated fields were removed; (d) the fields were evenly distributed in three groups based on their area, so that the group of smallest fields, *i.e.* smaller than 2.95 hectares, was discarded; and (e) in the final step, 20 fields were randomly selected for the medium and largest fields, *i.e.* 10 fields larger than 2.95 and smaller than 7 hectares for the medium category, and 10 fields larger than 7 hectares for the large category. The most complex fields and the fields with obstacles were excluded because their special geometry can increase the total harvest time per area (Oksanen, 2013), and consequently affect the study results. And the group of small fields was excluded because the produce of their high-quality areas, is too small to harvest selectively. This is because, considering an average yield of 7.62 t ha^{-1} for winter wheat (*Triticum aestivum* L.), which is the most common grain crop in Denmark (LF, 2020), and the chosen grain cart capacity of 10 Mg, a small sized field would not yield enough of the high quality grain to even fill half a grain cart. An overview of the location of the resulting set of fields is shown in Figure 20.

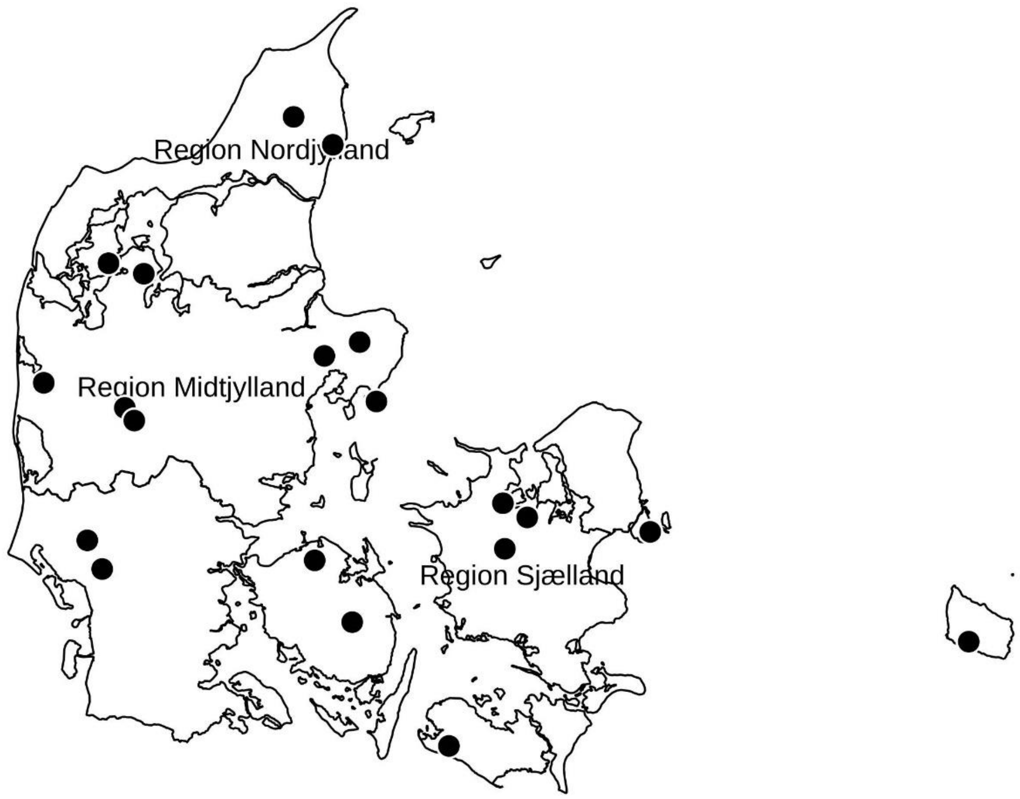

Figure 20. Spatial distribution of the selected set of fields across Denmark.

5.2.3 Quality areas creation

For this study, the high-quality areas were artificially created using the free and open-source Geographical Information System application QGIS v. 3.4.10, in order to provide a comparable set of data. In a real-world scenario, a quality map generated before the harvest operation would define the HQ areas to be harvested separately. It is implied that a reliable quality map can be created prior the harvest operation. For the comparative analysis three theoretical scenarios have been considered (Figure 21):

- Single Edged case (SE): one HQ area situated at the edge of the field so that at least two of its sides collide with the boundary of the field. In this case the HQ area could be considered a part-field or sub-field.
- Single In-field case (SI): the HQ area is collected into one bigger area inside the field.
- Twofold In-field case (TI): the HQ area is composed by two smaller areas inside the field.

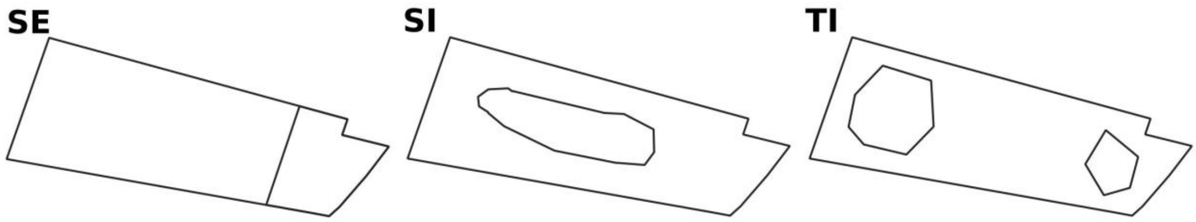

Figure 21. The three theoretical selective harvest scenarios studied in the paper shown for field M8 from the dataset. SE: single edged case; SI: single in-field case; and TI: twofold in-field case.

It has been designated that the HQ areas for the study should cover approximately 20% of the field total area. Smaller values than 20% would be too small to be harvested separately for a big part of the fields in the dataset. And higher values than 20% would make the in-field HQ areas, SI and TI, too big so that they would occupy most of the main field area, or would make them reach the field boundary, which goes against the definition of these scenarios. An overview of the set of fields and their hypothetical cases is presented in Figure 22 and Table 8.

Table 8. Field areas in hectares for the set of fields and the high-quality areas (HQ A) and remaining areas (Main A).

Field ID	Area A (ha)	SE		SI		TI		
		Main A	HQ A	Main A	HQ A	Main A	HQ A1	HQ A2
L1	8.45	6.83	1.61	6.72	1.72	6.75	0.80	0.89
L2	11.67	9.31	2.35	9.34	2.32	9.33	0.63	1.69
L3	8.98	7.17	1.80	7.15	1.82	7.16	1.24	0.57
L4	14.77	11.76	3.00	11.80	2.96	11.83	1.76	1.16
L5	8.56	6.77	1.79	6.84	1.72	6.83	0.78	0.95
L6	11.16	8.96	2.20	8.93	2.23	9.23	0.42	1.50
L7	7.03	5.57	1.45	5.62	1.40	5.61	0.87	0.54
L8	8.18	6.52	1.66	6.53	1.65	6.54	1.37	0.26
L9	32.29	25.82	6.46	25.83	6.46	25.84	4.75	1.68
L10	9.56	7.62	1.93	7.63	1.92	7.65	1.20	0.69
M1	2.96	2.37	0.59	2.34	0.62	2.41	0.14	0.41
M2	4.96	3.95	1.01	3.98	0.97	3.95	0.56	0.44
M3	6.55	5.24	1.31	5.23	1.31	5.23	0.94	0.36
M4	5.02	3.98	1.03	3.94	1.07	4.02	0.47	0.51
M5	5.46	4.38	1.08	4.33	1.13	4.38	0.13	0.94
M6	3.19	2.57	0.62	2.53	0.65	2.56	0.22	0.40
M7	6.18	4.95	1.22	4.94	1.23	4.94	0.72	0.51
M8	3.66	2.93	0.73	2.95	0.71	2.93	0.30	0.43
M9	6.83	5.44	1.39	5.49	1.33	5.46	0.99	0.37
M10	3.61	2.88	0.73	2.92	0.69	2.89	0.44	0.27

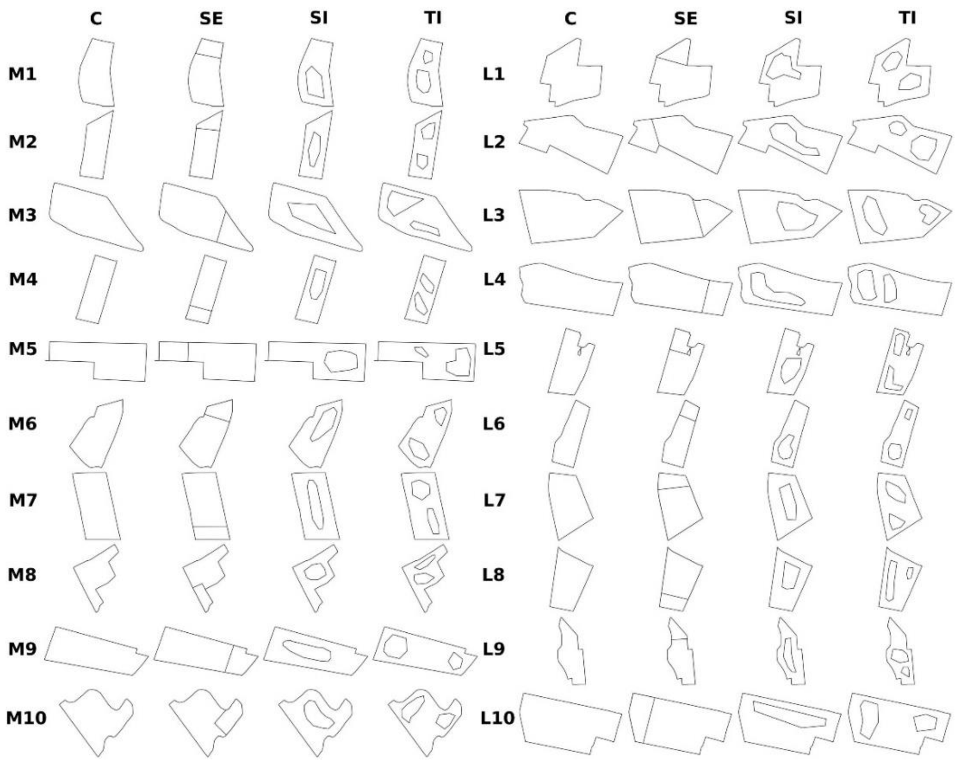

Figure 22. Overview of the set of fields and their distinct harvest cases.

5.2.4 Virtual capacity analysis

The harvest capacity was calculated in estimated hectares per hour for each case scenario and for each field in the dataset. The capacity analysis was based on the simulated operational time of the robot harvester to complete the operation. The results were then compared against each other to determine significant differences between the hypothetical cases previously described. To achieve this, a *t*-Test was applied between the medium and large sized fields, between conventional and selective harvest, between the SE case and the SI and TI cases, as well as between the SI case and TI case. A significance level of 0.05 was used in the analysis.

5.2.5 Virtual cost-benefit analysis

Along with the assumptions stated earlier, further assumptions for the cost-benefit analysis have been made: (a) the farm has the capabilities to store and sell the two different qualities of grain without directly implying additional costs; and (b) the total yield is the same in all scenarios studied for each field, so that the overall fuel consumption is only dependent on the harvest time. The cost-benefit analysis was determined by the operational costs to harvest each case scenario and field, and the benefits generated by selling the produce as a homogeneous product in conventional harvest or as high and lower qualities with corresponding prices. The operational costs per hour for the autonomous harvester robot have been estimated to 800 DKK h^{-1} for the medium sized field and 650 DKK h^{-1} for the large sized fields, based on the current Robotti operating capacity and harvest contracting services prices in Denmark. The cost differences are due to field size affects harvest efficiency (Xangsayasane *et al.*, 2019). A grain cart cost during harvest has been estimated to be 600 DKK h^{-1}. The total field output has been assessed to be the average yield for winter wheat in Denmark from the last five years, i.e. 7.62 Mg ha^{-1} (LF, 2020). As 90% of the wheat produced in Denmark is for animal fodder (Jørgensen, 2001), the prices used in the analysis correspond to fodder wheat. The average protein content for winter wheat in Denmark was 9.6 % (Sloth and Poulsen, 2020), which had an average price for 2020 of 1242 DKK Mg^{-1} (SEGES, 2021). The price premium for a protein content above 11% is 30 DKK in regard to values below 10% (DLG, 2017; VA, 2020), resulting in a price of 1272 DKK Mg^{-1}. The economic return per hectare for the three SH cases studied compared to the conventional harvest case was calculated by $(\Delta HC+\Delta HR)/A_f$, where HC are the harvest costs in DKK, HR the harvest revenue of SH in DKK, and A_f the field area in hectares. The HC were calculated by adding the operational costs per hour of the autonomous harvester robot and the two grain carts, multiplied by the harvesting time for each field. The HR were calculated by multiplying the average yield by the field part area being harvested and by the corresponding grain prices.

5.3 Results

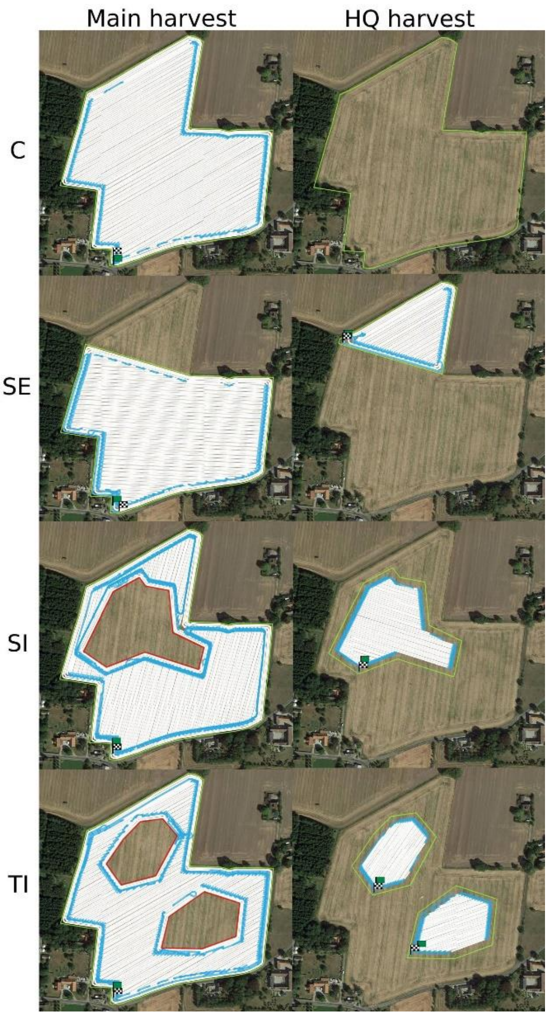

Figure 23. Route plans for field L1 for the four harvest cases, *i.e.* conventional (C), single edged case (SE), single in-field case (SI) and twofold in-field case (TI). White lines represent working paths and blue lines the connection paths.

Table 9. Detailed estimated harvest times in seconds of field L1 for the four harvesting cases and their field divisions.

Harvest time (s) for field L1							
C	SE		SI		TI		
Main	Main	HQ	Main	HQ	Main	HQ1	HQ2
7.20	6.05	1.76	9.10	2.14	8.09	0.97	1.10

Table 10. Detailed calculations of harvest costs and revenues in DKK of field L1 for the four harvesting cases.

Field ID	Harvest costs (DKK)				Harvest revenues (DKK)			
	C	SE	SI	TI	C	SE	SI	TI
L1	-8100	-8852	-9744	-9626	80001	80371	80396	80391

Table 11. Estimated harvest times for the four harvesting cases and the percentage of time increase for the SH cases compared to conventional harvest.

Field ID	Harvest time (hours) + pct. increase						
	C	SE		SI		TI	
L1	7.20	7.81	+8.4%	11.25	+56.1%	10.16	+41.0%
L2	9.51	9.71	+2.1%	11.80	+24.0%	12.32	+29.6%
L3	6.82	7.74	+13.5%	8.86	+29.8%	10.51	+54.0%
L4	10.71	11.44	+6.8%	13.29	+24.0%	13.84	+29.2%
L5	6.90	7.26	+5.2%	8.89	+28.9%	9.81	+42.2%
L6	8.95	9.63	+7.6%	10.99	+22.8%	9.31	+24.9%
L7	5.69	6.24	+9.7%	6.44	+13.2%	8.40	+47.7%
L8	6.80	7.29	+7.2%	8.30	+21.9%	8.38	+23.1%
L9	24.37	24.88	+2.1%	26.79	+9.9%	27.20	+11.6%
L10	7.70	8.11	+5.3%	8.75	+13.6%	10.59	+37.5%
M1	2.75	3.02	+9.9%	3.64	+32.7%	4.24	+54.4%
M2	4.07	4.72	+15.9%	5.00	+22.8%	6.13	+50.6%
M3	5.41	5.58	+3.2%	6.52	+20.6%	7.61	+40.6%
M4	4.06	4.49	+10.5%	5.15	+26.8%	6.30	+55.1%
M5	4.42	5.02	+13.6%	5.86	+32.4%	6.19	+40.1%
M6	2.81	3.16	+12.5%	4.63	+65.1%	4.84	+72.6%
M7	4.84	5.26	+8.8%	5.76	+19.1%	6.86	+41.8%
M8	3.71	3.71	+0.0%	4.85	+30.7%	5.71	+53.9%
M9	5.52	6.22	+12.8%	6.74	+22.1%	8.65	+56.9%
M10	3.68	3.78	+2.8%	4.97	+35.1%	4.77	+29.7%

In total 160 harvesting simulations were successfully run so that the operational times for each of the fields and each of the quality areas of the four different scenarios could be analysed (Figure 22 and Figure 23). Detailed harvest times and cost analysis for an example field, i.e. field L1 (Figure 23), are presented in Table 9 and Table 10. The harvest times for SH increased compared to conventional harvest in all SH cases but one, i.e. field M8 for case SE that equalled the conventional harvest time (see Table 11). The harvesting times for the SH case SE increased between 0.0% and 15.9% compared to conventional harvest, having an average increase for the medium sized fields of 9.0% and 6.9% for the large sized fields. Case SI increased between 9.9% and 65.1% the harvest time in regard to conventional harvest, with an average of 30.8% and 24.4% for the medium and large sized fields respectively. Case TI used between 11.6% and 72.6% more time than conventional harvest, spending in average 49.6% more time for medium sized fields and 34.1% for large sized fields (Table 11). Statistically significant differences were found between the harvest capacity of medium and large fields in all four cases (Table 12). Harvest capacities were also significantly different between conventional and all SH cases, as well as for SE compared to SI and TI cases. In the comparison between SI and TI SH cases, significant differences in harvest capacity were found for medium fields. However, no significant differences between harvest capacities were found between cases SI and TI among large fields (Table 12).

Table 12. Harvest capacities for the four harvesting cases studied and the field size groups, as well as t-Test (p > .05) applied to the harvest capacities.

Harvest case		Capacity scores (Ha h-1)		t-Test for harvest capacity			
				Large vs. Medium	C vs. SH	SE vs. SI and TI	SI vs. TI
		x̄	SD	p	p	p	p
Conventional		1.21	0.10				
	Large	1.26	0.06	-	-		
	Medium	1.16	0.10	.026	-		
SE		1.12	0.09				
	Large	1.18	0.07	-	.015	-	
	Medium	1.06	0.07	.003	.036	-	
SI		0.96	0.14				
	Large	1.02	0.11	-	.000	.003	-
	Medium	0.90	0.13	.046	.000	.005	-
TI		0.87	0.15				
	Large	0.97	0.13	-	.000	.000	.172
	Medium	0.78	0.09	.002	.000	.000	.038

Table 13. Total yields and economic returns for SH cases compared to conventional harvest.

Field ID	Yield (Mg)	Economic return per hectare (DKK ha^{-1})		
		SE	SI	TI
L1	64.41	-3	-264	-181
L2	88.93	35	-82	-111
L3	68.45	-21	-101	-221
L4	112.56	15	-67	-92
L5	65.29	21	-105	-175
L6	85.06	5	-73	-90
L7	53.58	-4	-23	-205
L8	62.40	8	-72	-79
L9	246.06	36	-3	-11
L10	72.85	19	-25	-151
M1	22.63	-32	-208	-385
M2	37.82	-64	-114	-307
M3	49.97	23	-98	-239
M4	38.26	-25	-135	-334
M5	41.67	-48	-176	-230
M6	24.37	-49	-438	-496
M7	47.12	-13	-81	-232
M8	27.94	46	-220	-418
M9	52.07	-41	-114	-344
M10	27.56	23	-259	-211

The cost-benefit analysis shows that for seven out of the ten large fields there is an economic return between 5 and 36 DKK ha^{-1} for the SH SE case, while for the medium sized fields only three out of ten have a positive economic return for the SE case, which is between 24 and 46 DKK ha^{-1}. Cases SI and TI do not have any positive economic return in the results of this study. SH case SE result in negative extra costs that range from -3 to -264 DKK ha^{-1} for the large fields and from -81 and -438 DKK ha^{-1} for the medium sized fields. The negative extra costs for harvesting selectively in case TI range from -11 to -221 DKK ha^{-1} for the large fields and between -211 and -496 DKK ha^{-1} for the medium sized fields (Table 13). Detailed harvest costs and revenues for an example field, i.e. field L1 (Figure 23), are presented in Table 10.

5.4 Discussion

Even though for one field, i.e. field M8, SH case SE presented no added harvest time (see **Error! Reference source not found.**), according to the results obtained SH affects significantly in all cases the harvest capacity when compared to conventional harvest (Table 12). This was an expected result as SH will in most cases increase the harvest time due to longer distances to be travelled. However, the results show that SH for some fields, e.g. Field M6 for case TI, it can increase the harvest time by more than 70% (see Table 11). Even if economically profitable, which it is not (see Table 13), this scenario would be unacceptable for most farmers, who are often greatly constrained by operational time schedules (Edwards, Bochtis and Søresen, 2013). Field area also affects significantly the harvest capacity between conventional and SH, due to the field area effects on harvest efficiency (Xangsayasane *et al.*, 2019). Regarding the SH cases studied, no statistical difference was found in harvest capacity for HQ areas that cover 20% of the large fields when they are distributed inside the field in one (SI case) or two areas (TI case). This is considered to be caused by the large size of the fields compared to the 3-metre working width of the harvester, which makes it possible for the optimised route planner to reduce the connection paths by segmenting the field into subfields when optimising the route to follow. The SE case is considered to be the optimal SH scenario because it allows dividing the field into subfields to be managed and harvested separately. This is already sometimes being applied when thoughtful farmers manage a farm (SmartAgriHubs, 2021). The SE case would also be easier to implement in contemporary farms without autonomous field robots. Even though the most complex fields were excluded when creating the field dataset (see Figure 22), field shape and the position as well as the shape of the HQ areas can have important effects on the total harvest times (Spekken and Bruin, 2013). The shape and position of the HQ area(s) can mean an increased number of rows and the segmentation of the main field area into subfields (see Figure 23), which eventually increase the total harvest time (see Table 9) and consequently increase the harvesting costs (see Table 10). In some specific cases SH was nearly as efficient as conventional harvest, while in other cases it increased the harvest time estimations in hours, above 50% more harvest time for many field cases (see field M6 in Table 11). Nonetheless, the theoretical SH cases presented here may not be the real cases encountered. The HQ areas modelled or measured for many fields can be scattered around the field and difficult to combine into HQ areas. A decision support system that evaluates harvesting times for different SH scenarios and prior harvest field tests for quality and quantity would aid the farm manager on decision making (Tozer and Isbister, 2007).

The harvest capacity results previously discussed need to be understood together with the cost-benefit analysis results, which show only minor positive revenues for some of the SE cases and greater losses for most fields in SI and TI cases. The little economic return resulted from the analysis of this study contrasts with the higher returns reported in other studies (e.g. (Tozer and Isbister, 2007; Meyer-Aurich *et al.*, 2008; Martin, Mccallum and Long, 2013; Whetton, Waine and Mouazen, 2018)). Corresponding with (Tozer and Isbister, 2007) analysis, the modest or negative revenues found in this study are influenced by grain price differences and the operational and logistics costs of harvesting and managing these HQ areas separately. The grain price differences used in the other SH studies range from more than double to more than ten times higher than the grain price differences used in this study (Farquharson, 2006; Martin, Mccallum and Long, 2013; Whetton, Waine and Mouazen, 2018). This affects the potential revenue of SH significantly. This can be caused by using in the analysis only fodder wheat price differences and not including premium prices for milling wheat. Including milling wheat prices in the comparison is not realistic in a Danish context as fodder grain cannot be destined for milling regardless of the protein content due to regulations. The man hour and machinery costs for harvesting in Denmark are also to be taken into account in the results, as they may be higher than in other contexts. Moreover, even if (Tozer and Isbister, 2007) included additional harvest distances in its operational cost calculations, none of the SH studies from literature have modelled the route planning time implications of SH that have been considered in this study. The additional times required for SH are an important factor to take into consideration because in some scenarios it can almost double the operational time. This study points out the necessity of including harvesting times in SH studies, which has not been done earlier in related work. It shows a contrasting reality for many scenarios compared to the results of related work; scenarios which farmers will often encounter in their fields. This study also uses a larger field dataset than the other studies related to SH, with the intention of addressing a larger variety of fields in regard to size and form. Consequently, the necessity to assess the implications of SH prior the operation is crucial, as shown by this study. Finally, it is needed for consideration that the robotic harvesting costs have been based on current conventional harvest costs. However, robotic autonomous harvesting could potentially reduce the operational costs per hour, which would benefit the SH results.

Nonetheless, in order to address sustainability issues, such as import of alternative protein sources, SH can still result in economic revenue in some cases. From the results, it is observed that the SE cases suppose for many fields little additional time than conventional harvest. SE cases are also harvested significantly more efficient than the other two cases. In addition, this type of harvesting method can also benefit of management practices like variable rate fertilizer application (Guerrero, Neve and Mouazen, 2021) that can enhance the output and more clearly define the HQ areas to be harvested separately.

In regard to the SH strategy followed by the autonomous harvester robot, the approach can also be applied to cases were harvesting lowest quality areas separately could increase the total average of the rest of the field to reach price premiums. A similar but alternative harvesting procedure could be harvesting the whole field simultaneously, but onload to different grain carts depending on the quality area the harvester is in. This would unavoidably require more grain carts involved in the operation as well as higher waiting times for them in the field with their subsequent costs, but could potentially reduce operation time compared to the method presented in this study.

Even though optimised route planning reduces the risk of negative impact of wheel traffic in the soil (Villa-Henriksen, Skou-Nielsen, *et al.*, 2020), it is necessary to mention that the SH strategy presented in this paper will inevitably increase the infield traffic, which can have consequent negative impacts on future crop yields (Chamen, 2015; Schjønning *et al.*, 2016; Obour, Keller, Jensen, *et al.*, 2019).The selection of assumptions made in this study were essential to make the results comparable. However, some assumptions may not fully represent the reality in many fields, e.g. uniform yield distribution, and some could inevitably affect the results, e.g. distance to storage. Not all farms have the capabilities of storing and selling different grain qualities, which is indispensable for SH. Distance to storage from the field will unavoidably affect the results, as they may require to increase the amount on grain carts or imply waiting times inside the field, which will automatically increase operational costs. This selected assumption represents an ideal but realistic scenario and is necessary for making the results comparable, as large distances will always affect negatively the economic return of the field (Lamsal, Jones and Thomas, 2016). A 20% HQ area is also an assumption that will affect the results if changed. Larger HQ areas will automatically improve the economic return of SH due to higher HQ yields, and the HQ areas would potentially reach the field boundary becoming the SE scenario, which has been proven to be harvested significantly more efficiently. Smaller HQ areas will predictably provide worse results for SH. Within the field, a uniformly distributed yield that has been assumed in this study to make a comparable dataset does not represent the reality of field crop yields. Within field yield variations are a fact acknowledged by farmers and in literature (e.g. (Ping and Dobermann, 2005; Lyle, Bryan and Ostendorf, 2014)). Furthermore, the long-recognised significant inverse relationship between yield and protein content (Terman *et al.*, 1969; Simmonds, 1995) implies that the HQ areas will have lower yield than the rest of the field, affecting the harvesting speed and fuel consumption because of differences in feeding rates and threshing power requirements (Tieppo *et al.*, 2019). Lower yields for the HQ areas would inevitably reduce the already marginal benefits and losses of selectively harvesting fodder winter wheat studied in this article in a Danish context. Another aspect to grain quality variability is the variability that is not captured by spatial quality maps (Leroux and Tisseyre, 2018), i.e. the variability within the mapping resolution, within the working width of the harvester or even within the grain spike. For addressing this variability, only grain segregation during harvest or after harvest can accomplish the task. However, this strategy relies on sensors that are very challenged to monitor the grain stream and a diverter valve that needs to react fast enough to segregate the grains. A task that cannot be relied upon with the current technological development state. These selected assumptions in the study intend to simulate realistic farm scenarios or are required to make the results comparable. The results with the given assumptions still provide an insight of SH applied to a Danish context in general. For a specific field, it is always recommended to make a pre-harvest assessment to study the feasibility of SH, which may be profitable in certain cases.

In different contexts, where the grain price differences are higher and the harvesting costs lower than in Denmark, SH can be an interesting option to feasibly increase the economic return of some fields. The ideal position of the HQ areas for higher economic returns is represented by case SE, where the edges of one HQ area reach the field boundary and cover at least 20% of the field area creating minimum reduced operational efficiency. In those scenarios SH is expected to be feasible. Nonetheless, it is always required to study each field based on reliable grain quality maps to assess the viability of SH for that field.

Further research is required to address the potential benefits of SH with autonomous agricultural robots, where the route planning involves actively the grain carts so that the whole field is harvested in one go, but the grain carts are assigned to the harvester depending on the grain quality area it is located on. The influence of grain price differences and harvesting costs should be addressed too as they truly determine the economical return of SH. Finally, the influence of the size, shape and location of the HQ areas with respect to the field boundary could be interesting to study as the results presented in this article show how much HQ areas location and distribution affect the harvest capacity.

5.5 Conclusion

Selective harvesting has been studied for an autonomous agricultural robot in a Danish context for harvesting fodder winter wheat and for its potential to reduce the amount of imported alternative protein sources. The optimized route planning tool from the autonomous field robot, Robotti, employed in the study was able to generate routes for all the fields and cases of the dataset. Taking into consideration the selected assumptions, selective harvesting by harvesting separately high-quality areas (based on protein content) from the rest of the field is not economically feasible in a Danish context. The results showed significant differences in harvest capacity between conventional and selective harvest. The field shape as well as the location, shape and distribution of the high-quality area(s) had a significant influence on the SH capacity. These negative results for SH were affected by the small price differences of fodder wheat regarding protein content considered in this study. The high harvesting costs considered in the simulations had an influence too. In different contexts with higher grain price differences and lower harvesting costs, SH is expected to be economically feasible for the case SE, where the HQ areas reach the field boundaries and cover at least 20% of the field area. Additional research on the influence of grain price differences as well as harvesting costs, on the specific influence of shape and location of the HQ areas, and different route planning strategies will provide improved insight of the possibilities of SH performed by autonomous field robots.

Chapter 6 General discussion

In this chapter, the main contributions and conclusions from the chapters 2, 3, 4 and 5 are assessed taking into consideration the objectives of the Ph.D. project. The research contributions that addressed the identified knowledge gaps are evaluated and contextualised within the state-of-the-art.

6.1. Internet of Things in arable farming and optimised route planning

Chapter 2 focussed on reviewing the implementation, applications and challenges of the IoT in arable farming, which has some distinct characteristics that are unique compared to other farming systems and had not been addressed before. The exhaustive reviewing process included the considerations made by 167 research articles in the implementation and applications of IoT technologies in arable farming, as well as field operations surveillance and optimisation. Having in mind the interdisciplinary viewpoint, the broad focus on arable farming in general covered the perspectives of diverse disciplines and specialities in the employment of IoT in such a context. An exclusive review paper on optimised route planning in arable farming would have missed some of the considerations and challenges identified by other applications, which could potentially benefit the considerations made for the implementation of a harvest fleet route planning system. Furthermore, as little information about the practical implementation of optimised route planning for field operations was available, the broad perspective was required. Additionally, the review paper thoroughly covered the challenges found in the implementation of IoT in agriculture in a systematic manner and proposed solutions to each of them, which has not been done so methodically in previous reviews. The review can therefore aid other researchers identify unaddressed challenges and may show potential future areas of research.

From another point of view, the review paper drew attention to this generally overlooked subject in most reviews about IoT in agriculture, which is optimised route planning and monitoring of field operations. This subject has either not been included (Stočes *et al.*, 2016; Ray, 2017; Talavera *et al.*, 2017) or only slightly mentioned (Verdouw, 2016b; Tzounis *et al.*, 2017) in the previous reviews. Therefore, a whole section in the review paper was dedicated to this relevant application of IoT technologies. This is especially pertinent with the current and near future employment of autonomous agricultural vehicles (Moysiadis *et al.*, 2020; Araújo *et al.*, 2021).

6.2. Implementation of a harvest fleet route planning tool

A practical solution for the integration and implementation of a harvest fleet route planning tool was proposed in chapter 3. The solution employed smart Android devices with multifunctional purposes: data handling, gateway and graphical user interface. The Android devices were connected through the internet with a server and a web application. Only a few examples of vehicle and operation live monitoring have been described in literature (Pfeiffer and Blank, 2015; Oksanen, Linkolehto and Seilonen, 2016), however they did not include any route planning features, which requires some additional features and computational power. Therefore, the solution proposed in this conference paper, which described the practical implementation of the optimising and monitoring tool for harvesting operations, covered a gap in literature. Furthermore, the solution described also addressed the integration of the innovative route optimisation model combined with the technology requirements for its implementation, as well as its practical application.

The Android devices used had sufficient computing resources to execute the route optimisation calculations and dynamic rerouting of the vehicles. These devices provide a flexible and scalable solution that can work across manufacturing brands (Hernandez-Rojas *et al.*, 2018). And it is that interoperability across brands that is often the biggest challenge (Brewster *et al.*, 2017). Even though the ISO 11783 standards and the ISOBUS components are currently supported by agricultural machinery producers, it is only meant to link tractor and implement through a wired connection (Oksanen, Piirainen and Seilonen, 2015). A practical challenge of the system proposed is that the use of Android devices adds a new screen for the operator to look at, besides the on-board computer(s) in the machine cabin. It is therefore not the optimal solution. An integrated tool in the terminals of the machines could increase the computational capacity of the optimisation tool and reduce the number of screens to look at. However, it would require the use of widely adopted standardised formats that are integrated in the systems across brands, and this is currently not the case. Some attempts to standardise machine agricultural data across manufacturing brands are being made. The ADAPT framework is aiming to become the standard format in agriculture (Brewster *et al.*, 2017), but it is an offline solution. And the Agricultural Industry Electronic Foundation (AEF) standard organisation is developing the EFDI (Extended Farm Management Information Systems Data Interface) for seamless communication between ISOBUS machines and FMISs, but it is still under development (AEF, 2020). In a similar manner, FIWARE, the platform promoted by the European Union, is aiming for an IoT-enabled smart farming solution that includes farm machines (Rodriguez, Cuenca and Ortiz, 2018), but is still not fully developed. Therefore, the solution presented in chapter 3 is considered to be the adequate in the current state of smart farming.

Another important aspect of the solution proposed is the location of the computations. The harvest fleet route planning system used edge-computing in order to increase operational efficiency and reduce potential latency problems when communicating the data caused by limited mobile network connection. The edge devices for the computations were the same devices in charge of the data handling and visualising the solution, *i.e.* the Android devices, thus increasing the efficiency of the system. Additionally, edge computing can reduce to the minimum the amount of data transferred through the internet (Ferrández-Pastor *et al.*, 2016) and consequently ensure minimal delays in the dynamic rerouting of the vehicles involved during the harvesting operation. However, the amount of data transferred is not big enough to become an issue, as it is only a few KB s^{-1} of text. A cloud-computing solution could be a valid alternative option. In the cloud, a high-performance computer cluster can be assigned to process the computations required for the harvest fleet route planning, allowing faster completion times (Seyyedhasani, Dvorak and Roemmele, 2019). Software updates and logging of errors are also easier to manage with a cloud solution. Nonetheless, both edge and cloud computing solutions require internet connection, which is not always available in rural areas. To solve this, wireless vehicle-to-vehicle communication would be necessary. 5G, the latest generation of mobile communications, can solve this problem once it is widely adopted as it allows vehicle-to-vehicle communication (Marsch *et al.*, 2016). Once 5G is widely adopted, further studies would be required to address the functionality of the systems in areas with reduced internet connection.

Finally, the optimisation goal of the algorithms can vary significantly, as described in the introduction. The harvest fleet route planning tool described in this study aims to minimise the total harvest time, while many other solutions proposed in literature aim to minimise the non-working distances of the harvester (Bakhtiari *et al.*, 2013; Bochtis *et al.*, 2013; Conesa-Muñoz, Pajares and Ribeiro, 2016; Utamima, Reiners and Ansaripoor, 2019). Reducing non-working distances to a minimum may translate into total operation time reductions, but not necessarily always. As harvest operations involve the collaboration of a fleet of vehicles, the grain carts involved may not always be readily available to receive an unload. This is because in many real-world situations, grain carts have to drive outside the field, where on-farm offloading or traffic related situations can result in important delays. During these delays, the harvester may end waiting motionless in the field for unloading its full grain tank. As harvesting operations are very costly (Basnet, Foulds and Wilson, 2006; Plessen, 2019), reducing the total harvest time is more appropriate. Because the vehicles are constantly being monitored, when the tool calculates grain cart delays, it will redirect the harvester to work an alternative route than may be longer in distance, *e.g.* rows at the opposite side from the gate, but that will avoid the harvester to wait for an unloading event. This will result in an overall operational time reduction with its corresponding costs savings.

6.3. Harvest fleet route planning in risk of soil compaction reduction

Chapter 4 addressed the environmental perspective of the use of a harvest fleet route planning system. Due to the important negative environmental impacts of wheel trafficking on the soil, *e.g.* nutrient leaching, green-house-gas emissions and erosion (Vermeulen and Mosquera, 2009; Chamen, 2015; Bogunovic *et al.*, 2018), as well as the negative impacts on the crops (Alblas *et al.*, 1994; Chen and Weil, 2011; Obour, Keller, Jensen, *et al.*, 2019), the traffic associated with harvesting operations was studied. In the chapter, the recorded traffic produced by all the vehicles involved in harvesting operations are compared to the traffic produced if a harvest fleet route planning tool was being employed. The article addressed the environmental perspective of an optimisation tool which goal is not directly intended to minimise the risk of soil compaction, as the solutions proposed by Bochtis, Sørensen, & Green (2012) and Gorter (2019). In contrast, the aim of the tool studied was to reduce overall harvest time, which is often the main goal of farm managers and contractors (Basnet, Foulds and Wilson, 2006; Plessen, 2019). The results show a reduction of traffic occurrences in all the fields studied, especially because the tool timely coordinates the unloading events making the grain carts drive efficiently to the harvester when needed. However, the study showed that regarding repeated traffic the tool did not always perform so well, because the in some scenarios the system may direct a grain cart or the harvester in a route that results in more repeated traffic if that means operational time reductions. The use of the tool also resulted in higher maximum traffic loads per grid cell, mainly because the optimisation tool filled the grain carts to the maximum. Nonetheless, the results confirmed that harvest fleet route planning can be employed in the soil compaction mitigation strategies of a farm. This had only been mentioned by previous research articles, but had not been studied yet.

The harvest fleet route planning tool can be adapted to reduce traffic in the main field area by adding specific trafficability constraints, *e.g.* controlled traffic farming, or by choosing an optimal driving direction that reduces overlapping instead of reducing manoeuvring. These changes could affect the overall goal of reducing harvesting time, but the additional time may be small compared to the benefits of reducing the in-field traffic. Further investigations on how the driving direction and different trafficability constraints affect harvest times and in-field traffic would be required. Finally, if a risk of soil compaction map was to be included in the route planning optimisation algorithms, cost functions that take into consideration the maps and the vehicle tank capacities would be necessary in the calculations. However, if the tool employed does dynamic rerouting, as the system presented in chapter 3, experienced machine operators could alter the route to avoid for example wet areas, so that the human-in-the-loop would collaborate for a joint effective solution.

6.4. Optimised route planning in selective harvesting

The aim of chapter 5 was to address the potential application of optimised route planning for selective harvesting. Selective harvest has the intention of generating higher economic returns for a field by harvesting the crop separately based on the quality of the grain in order to capture grain price premiums. In literature the economic effects of altering the route of the vehicles involved in selective harvest has not been fully explored before. The results of this study show that in a Danish context the price differences in quality are too small to make selective harvest economically feasible. The main cause for these small price differences is that Denmark produces mainly fodder grain, which is much cheaper than grain for human consumption (LF, 2020). The results also demonstrate that even though the harvest capacity is significantly affected in all the selective harvest scenarios studied, in some specific cases the additional harvest time is negligible. It is assumed therefore that in other contexts with high grain price differences and lower harvesting costs, the economic return would be interesting enough for farmers to adopt it. Nevertheless, the study provides a new perspective on how selective harvest affects the harvesting route with its subsequent economic penalties. The study also offers a more realistic view on selective harvest that shows that in many cases, selective harvest is not profitable for the farmer an should be only targeted by careful economic feasibility studying prior the operation (*e.g.* SmartAgriHubs, 2021).

As the study proposed three different quality map scenarios, the results clearly demonstrate that one case has more potential for selective harvest than the other two cases. When the quality area reaches the boundary of the field, this area can be harvested independently as a subfield. This selective harvest scenario decreases the harvest capacity only by 0.04 Ha h^{-1} for the larger fields and by 0.1 Ha h^{-1} for the medium sized fields. The reduction in harvest capacity is equivalent to or better than the reduction observed between conventional harvest of larger and medium sized fields, which is 0.1 Ha h^{-1}.

The approach to selective harvest presented in the study consisted in harvesting first one area and thereafter the other. Harvesting both at the same time by not altering the harvester route but emptying the grain tank every time a new quality area is reached, could potentially reduce the total harvest times. However, it would imply the use of at least one more grain cart. Future research on this alternative approach is necessary to address its potential benefits.

The article also offers some insight into the application of autonomous field robots to perform field operations. The route planner employed for the simulations is currently employed by an autonomous field robot in diverse operations. As smart farming is employing more automation and robotics in field operations (Moysiadis *et al.*, 2020; Araújo *et al.*, 2021), new approaches compared to the traditional operations can be applied. These alternatives, such as strip cropping or selective harvesting, may require complex routes to be followed by the vehicle, which can be very challenging for a human operator, but are not so for an autonomous vehicle. These new approaches can benefit farming and the environment in new ways that require assessment.

6.5. Interdisciplinary approach to harvest fleet route planning

The overall aim of the study presented in this Ph.D. dissertation was to provide an interdisciplinary perspective to harvest fleet route planning centring the attention on the implementation, *i.e.* the technological aspect, and different applications of the system by looking into the agronomic, environmental and economic aspects of them. These other aspects of optimised route planning, *e.g.* vehicle routing problem, in agricultural operations (Bochtis and Sørensen, 2009), have either not been addressed yet or only to a limited extent. Until recently, the main focus has been the mathematical optimisation and variants to the problem, but to the author's knowledge the technologies required for the physical implementation of such a system have not been addressed. And regarding the applications, some studies have looked into some of the environmental aspects of it (Bochtis, Sørensen and Green, 2012; Rodias *et al.*, 2017; Gorter, 2019) but still focusing on the optimisation method employed to address a specific goal. The economic aspect has been presumed based on the time or the distance reductions made by the methods used (Conesa-Muñoz, Pajares and Ribeiro, 2016; Edwards *et al.*, 2017; Utamima, Reiners and Ansaripoor, 2019) but the field datasets used in the analysis were too small to draw tangible conclusions that are applicable for farm managers (Barnes *et al.*, 2019). Additionally, the economic return per unit area of optimising the harvest route has not been addressed yet. Therefore, chapter 3 made a proposal for the implementation of an optimised route planning tool for harvest operations from the technology point of view; chapter 4 aimed to cover the environmental aspects of risk of soil compaction reduction of a harvest fleet route planner that aims to reduce operational time; and chapter 5 covered the route planning economic implications of selective harvest. These are perspectives that integrate different scientific disciplines and have not been studied yet.

Even though the technology maturity and economic returns from smart farming technologies are the main drivers for their adoption (Day, 2011; Ren and Martynenko, 2018; Barnes *et al.*, 2019), the social aspect is still an important aspect to be considered (Sørensen *et al.*, 2010; Barnes *et al.*, 2019; Moysiadis *et al.*, 2020). The social aspect covers not only the acceptance and adoption of the technology, but also the social implications that it may have (Bechtsis *et al.*, 2017). The social perspective is also relevant in many interdisciplinary studies (Macleod and Nagatsu, 2018; D'Este *et al.*, 2019); however, it has not been directly addressed in this study. Nonetheless, it has been informally considered during the physical tests of the harvest fleet route planning system through unstructured conversations, whose feedback was considered in the discussion section of each chapter. In general, the route optimising tool received positive feedback from the operators and farm managers, but desired integration of the tool with the on-board computer in the cabin, confidence in the economic return of an eventual investment and robustness of the whole system. These considerations match overall with the main factors affecting the adoption of precision agriculture technologies in Europe (Barnes *et al.*, 2019).

The environmental perspective is also crucial due to the global need to increase food production and at the same time reduce its environmental impacts (Godfray *et al.*, 2010; Tilman *et al.*, 2011; Crist, Mora and Engelman, 2017). Furthermore, as financial incentives from governmental institutions play a big role in adopting smart farming technologies (Barnes *et al.*, 2019), these public institutions do not only aim to increase the economic benefits of agriculture but also to jointly reduce its environmental impacts. Consequently, chapter 4 addressed the environmental effects of harvest fleet route planning in the soil structure.

The perspective of different disciplines was employed in this study to achieve a more interdisciplinary view of optimised route planning in harvest operations. These perspectives were missing or were limited in literature, and needed therefore more research, which this Ph.D. project has provided. More future research from perspectives from different disciplines is still necessary on optimised route planning generally and harvest fleet route planning specifically. More potential applications need to be implemented and evaluated on large field datasets so that the environmental and economic benefits are confirmed. These route planning systems are becoming currently even more relevant with the arrival of commercial autonomous field robots, stressing the necessity of more interdisciplinary research on these tools.

Chapter 7 Conclusions

An interdisciplinary approach to harvest fleet route planning was assessed by looking into the technological requirements for its implementation, and into the environmental effects on soil from the application of the optimisation tool and the economic effects of employing the tool in selective harvest. The conclusions made from the different disciplinary perspectives are here summarised:

- The role of the Internet of Things in arable farming and on route planning in field operations was reviewed. The methodical focus on implementation, applications and their challenges provide new insights for further research studies in arable farming and field operations.

- A proposal for the implementation of a harvest fleet route planning tool is made. The Android based system dynamically reroutes the vehicles when alterations to the plan occur. The system is tested during harvest operations and is capable of monitoring and planning routes for the harvester and grain carts.

- The risk of soil compaction resulting from vehicle traffic during harvest operations is assessed. Even though the harvest fleet route planning tool aims to reduce operational time, it reduces traffic occurrences in all fields compared to conventional recorded operations. From the results it could be concluded that these optimised route planning tools can be used as part of the soil compaction mitigation strategy of a farm.

- Optimised route planning was employed to evaluate the economic effects of altering the route in selective harvesting. Different scenarios were studied and compared with conventional harvest using autonomous field robot simulations. In general, selective harvest was not economically profitable for the cases studied due to small grain price differences, even if the harvest capacity is little affected in some of the scenarios.

- Overall perspectives from different disciplines to harvest fleet route planning were provided. There is a need to continue to explore the implementation and potential applications as well as benefits of these tools by interdisciplinary viewpoints.

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Appendix

In-field traffic management

Ole Green[b,c], Alevtina Evgrafova[b], Søren Kirkegaard Nielsen[b], Gareth T.C. Edwards[b], Andrés Villa-Henriksen[a,b], Liubava Znova[b], Frederik Foldager[b,d], Lars Juhl Munkholm[c] and Tommy Dalgaard[c]

[a] *Aarhus University, Department of Electrical and Computer Engineering*
[b] *Agro Intelligence ApS*
[c] *Aarhus University, Department of Agroecology*
[d] *Aarhus University, Department of Mechanical and Production Engineering*

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In order to improve energy use, reduce operational costs and minimise negative environmental impacts (*e.g.* soil compaction) induced by intensive heavy-machinery traffic, it is necessary to define and implement suitable operational management strategies. Different strategies have been proposed for infield traffic management with emphasis on: (i) the vehicle or implement, *e.g.* tyre inflation regulation on the go via tyre pressure monitoring system as well as the use of lighter and/or smaller autonomous self-propelled implements (Green et al., 2014); (ii) on-land ploughing instead of in-furrow ploughing; (iii) soil conditions, *e.g.* soil readiness modelling or optimised route planning in order to reduce soil compaction. While some of these strategies are already widely known and adopted by concerned farmers, others are still needed further development and strategic implementation. Considerable attention has been paid to optimised route planning as the strategy that can mitigate soil compaction issues and minimise operational time and costs, hence, following sustainable soil management practices as well as be easily combined with other strategies for manging in-field traffic.

The driving route in the field has traditionally been based on the decision capabilities of the vehicle operators, *i.e.* the driver decides on the best route to complete a field operation in a minimal time or based on some criteria stated by the farmer, *e.g.* wildlife avoidance planning. However, current research (Bochtis, Sørensen, & Busato, 2014) and industrial products (Edwards et al., 2017) are developing systems for optimising route planning automatically. Optimised route planning calculates an optimised route for each field adaptively according to the vehicles' behaviour using combinatorial optimisation algorithms. The criteria used for the optimisation can include, besides the reduction of operational time, geo-referenced information that can be used for the variable rate application or/and section control. In order to utilise geo-referenced information and achieve higher farming precision by taking the within-field spatial and temporal variability into account, Global Navigation Satellite System (GNSS) technologies should be used during field operations. Thus, the in-field optimisation can be achieved by simulating planned agricultural operations using the algorithms based on the predictions of the shortest total, headland, and refill timing and distances, soil compaction, while the site-specific field characteristics and agricultural applications (*e.g.* fertilizer) and features of the fleet vehicles (*e.g.* tank and carrying capacities) are taken into account. Moreover, optimised route planning can be applied to various agricultural operations and, especially, valuable during the operations with intensive heavy traffic such as slurry application or harvesting, hence, reducing the negative impacts of traffic intensity. Furthermore, auto-steering systems will improve the operational performance as this system will allow following the path and adapting more precisely to the spatial variability than a traditional human-based steering.

A fleet logistics optimization tool can also include other optimisation criteria such as the operational speed, turning trajectory, however, if traffic intensity is a main parameter for route optimisation, the operational distance and time will be significantly reduced as the number of passes per area as well as the total weight by traffic per area (both accumulated and at the specific time) can be reduced. Moreover, the optimal strategy in order to follow sustainable soil management practices would be combining as many strategies as possible as well as finding a possibility to combine various operational functions, usually provided by multiple vehicles, in one vehicle with field data recording. The data, collected using agricultural vehicles, can be shared using Internet of Things (IoT) technologies and will provide valuable information for soil management practices and following operations. Thus, full automation of field operations can provide even more accurate measures for reducing production costs while operating in an environmentally sustainable manner, *e.g.* optimising fleets of light-weighted robots for most, if not all, field operations.