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USING THE VEHICLE ROUTING PROBLEM (VRP) TO PROVIDE LOGISTICS SOLUTIONS IN AGRICULTURE

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USING THE VEHICLE ROUTING PROBLEM (VRP) TO PROVIDE LOGISTICS SOLUTIONS IN AGRICULTURE

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Engineering at the University of Kentucky

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2017

ABSTRACT OF DISSERTATION

USING THE VEHICLE ROUTING PROBLEM (VRP)
TO PROVIDE LOGISTICS SOLUTIONS IN AGRICULTURE

Agricultural producers consider utilizing multiple machines to reduce field completion times for improving effective field capacity. Using a number of smaller machines rather than a single big machine also has benefits such as sustainability via less compaction risk, redundancy in the event of an equipment failure, and more flexibility in machinery management. However, machinery management is complicated due to logistics issues.

In this work, the allocation and ordering of field paths among a number of available machines have been transformed into a solvable Vehicle Routing Problem (VRP). A basic heuristic algorithm (a modified form of the Clarke-Wright algorithm) and a meta-heuristic algorithm, Tabu Search, were employed to solve the VRP. The solution considered optimization of field completion time as well as improving the field efficiency. Both techniques were evaluated through computer simulations with 2, 3, 5, or 10 vehicles working simultaneously to complete the same operation. Furthermore, the parameters of the VRP were changed into a dynamic, multi-depot representation to enable the re-route of vehicles while the operation is ongoing.

The results proved both the Clarke-Wright and Tabu Search algorithms always generated feasible solutions. The Tabu Search solutions outperformed the solutions provided by the Clarke-Wright algorithm. As the number of the vehicles increased, or the field shape became more complex, the Tabu Search generated better results in terms of reducing the field completion times. With 10 vehicles working together in a real-world field, the benefit provided by the Tabu Search over the Modified Clarke-Wright solution was 32% reduction in completion time. In addition, changes in the parameters of the VRP resulted in a Dynamic, Multi-Depot VRP (DMDVRP) to reset the routes allocated to each vehicle even as the operation was in progress. In all the scenarios tested, the DMDVRP was able to produce new optimized routes, but the impact of these routes varied for each scenario.

The ability of this optimization procedure to reduce field work times were verified through real-world experiments using three tractors during a rotary mowing operation. The time to complete the field work was reduced by 17.3% and the total operating time for all tractors was reduced by 11.5%.

The task of a single large machine was also simulated as a task for 2 or 3 smaller machines through computer simulations. Results revealed up to 11% reduction in completion time using three smaller machines. This time reduction improved the effective field capacity.

KEYWORDS: Vehicle Routing Problem, logistics, effective field capacity, field efficiency, Tabu Search

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August 20, 2017

USING THE VEHICLE ROUTING PROBLEM (VRP)
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August 20, 2017

To my wife Paria, and parents, I could not have done it without you.
Thanks for all the love and support along the way …

&

To …

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CHAPTER 1: INTRODUCTION

Farmers are limited by the amount of field work they can complete within a specified time window. This is called Effective Field Capacity, which according to the definition is the total area worked divided by the time until the field was complete. As such, reducing the time for field completion which is considered a holy grail in agricultural operations will be accomplished through improving effective field capacity (American Society of Agricultural and Biological Engineers, 2011).

There are essentially only two ways to increase effective field capacity – increase speed, width or size of individual machines or use additional machines at one time.

1.1 SINGLE VEHICLE

Increasing speed or width of machines is a frequently used approach to improving effective field capacity as evidenced by the increasing size and horsepower of agricultural machinery over the decades (Shearer, Pitla, & Luck, 2010b). In addition to making these machines larger and faster, much research has focused on improving their efficiency by discovering algorithms that divide a field into paths in such a way to minimize turning and other non-productive time (D. D. Bochtis & Vougioukas, 2008; I. Hameed, D. Bochtis, C. Sørensen, & M. Nøremark, 2010; Jin & Tang, 2010; Oksanen & Visala, 2009). Although larger, faster machines have significantly improved capacity over time, researchers have identified compaction issues with making even larger machines (Blackmore, Have, & Fountas, 2002; Hamza & Anderson, 2005). They also are less flexible in smaller or fields with complex geometry. In addition, it is probable that obsolescence should be considered with respect to newer technologies, and as such, it effects the vehicle life (Shearer et al., 2010b). Therefore, it cannot be expected that substantial improvements in bigger and faster agricultural machinery will continue (Dionysis D Bochtis, Sørensen, & Busato, 2014).

1.2 MULTIPLE VEHICLES

The other method of increasing effective field capacity is to increase the number of machines being used at one time (Blackmore et al., 2002; Shearer, Pitla, & Luck, 2010a). In many situations, using multiple vehicles in the same environment is a good strategy to handle very complex problems. Agriculture is one of the contexts where multiple vehicles are applicable. Current advances in innovative sensing and information and communication technologies have paved the way for introduction of autonomous vehicles and intelligent machines into agricultural operations. This breakthrough will alleviate the environmental impact of agricultural machinery and improve efficiency (Dionysis D Bochtis et al., 2014). Using multiple machines allows the use of smaller machines with less compaction risk. It also provides redundancy in the event of an equipment failure and more flexibility in machinery management. And another significant benefit to follow the use of smaller machines on the farm will be the ability of manufacturers and producers to reduce the liability of fully autonomous machines (Blackmore et al., 2002). As such, there are demands pushing towards operating a larger number of smaller vehicles.

1.3 CHALLENGE OF MULTIPLE VEHICLES

1.3.1 Path Planning

In order to take full advantage of these advances and new paradigm in agriculture it is essential to increase utilization of the machinery for agricultural operations. To this end, intelligent and optimized path planning and task scheduling for vehicles must be provided rather than the traditional agricultural operations planning. There are several common approaches used by farmers currently to cover the whole field by a fleet of vehicles. In one approach, vehicles follow each other with the following vehicle working the next pass over. This method is okay for two, but coordination becomes difficult and a big issue for a human operator when many vehicles are used. They also waste time driving by all the rows just completed by neighboring vehicles. Another approach is dividing the field into zones and each vehicle starts working in a zone, this method is so-called “work-zone”. Therefore, since for the both currently most used approaches human is involved in coordination, there will be difficulties in well path assignment to each vehicle. However, systems of multiple vehicles engaged in a collective behavior to carry out an overall task are an important challenge. The big challenge in using multiple machines together is coordinating their actions so they efficiently finish their tasks. This issue ends up being even more complex for fields with irregular and non-convex shapes.

According to the ASABE Standards (ASABE & EP496.3, 2006), helpful engineering information in making management decisions on farms consists of tractor performance, machine power requirements, field machine performance, cost of use, reliability, selection of field machine capacity, and replacement. In management of agricultural machinery there are five management tasks by which various management levels of operations on the farm are encompassed. These tasks are capacity planning, task times planning, scheduling, route planning, and performance evaluation (Dionysis D Bochtis et al., 2014) . However, the category of replacement concerns economic issues and is not paid attention to through those five tasks. Scheduling and route planning as two of the main five topics in management of agricultural machinery should be taken into consideration to enable producers to benefit from multiple machines utilization.

1.3.2 Task Updating for Vehicles

One of the main advantages of exploiting a number of vehicles in the field is flexibility in assigning tasks to each vehicle owing to redundancy of vehicles in the field, since uncertainty is inherent in agricultural operations. As opposed to using one big and fast machine, envision a situation in which either farmer decides to utilize one or some of the vehicles of the fleet performing a task for other operations, or one of the vehicles breaks down and should be taken out of the field, thanks to communications and control technology coupled with widespread availability of Global Navigation Satellite Systems (GNSS) using multiple vehicles empower the farmers to manage the situations by assigning the tasks of the removed vehicles to those available on the field. Whereas carrying out the tasks with a large vehicle wouldn't provide flexibility for the farmers in the former case, and it would be expensive in terms of money and time, in the latter case.

In management of agricultural operations, there are countless situations where producers act to reassign tasks to vehicles due to availability of equipment or even a piece of land. Putting these into perspective, consider the vehicle or vehicles in the prior scenario which were pulled out for another operation finished their task and now they are out of work such that the farmer wants to re-utilize them in the current operation in progress, or the broken machine is repaired and ready to resume working in the field. In order for such scenarios to be handled it is required to view the problem from the perspective of dynamic vehicle routing i.e. input data are continually updated.

1.4 OBJECTIVES

The overall goal of this project was to provide logistic solutions for area coverage when a fleet of vehicles are used in agricultural operation using the Vehicle Routing Problem (VRP). All things considered, in order to address the above mentioned issues with respect to improving effective field capacity and accomplish the project goal, we pursued four distinct objectives as follows:

1- Transform the Agricultural Field Coverage Problem into a standard Vehicle Routing Problem (VRP).

Hypothesis: It is possible to change the Agricultural Field Coverage Problem with multiple vehicles into a solvable Vehicle Routing Problem.

2- To change the parameters of VRP to enable to update the route of each vehicle during an operation.

Hypothesis: Dynamic re-routing of the vehicles involved in an operation can be conducted while keeping the field work parameters such as effective field capacity and field efficiency similar to the pre-determined solutions.

3- Compare "optimal" results from VRP with the conventional farmer methods.

Hypothesis: Computerized path assignment through optimization yields more efficient solutions compared to the current farmer path allocation techniques in terms of completion time.

4- Compare the efficiency of replacing a single large vehicle with multiple smaller vehicles.

Hypothesis: Dividing up the task of a big machine into the task of a number of smaller machines is more efficient, in a complicated field, with respect to completion time and will improve effective field capacity.

1.5 DISSERTATION OUTLINE

This dissertation is organized in five chapters. Chapter 1 establishes the general rationale and justification of this research and identifies the specific objectives that will be addressed within this dissertation. Chapter 2 starts with converting and representing a field area coverage into a standard Vehicle Routing Problem (VRP). Then it continues with two different approaches to provide solutions for the VRP problem. In chapter 3 management of agricultural machinery was addressed. Three different most commonly scenarios— 1) changes in the number of vehicles 2) unexpected field work rates 3) changes in the area to be worked — in utilizing multiple vehicles were investigated. Solution to these scenarios were provided through the re-allocation of task to the involved vehicles. Chapter 4 examines the feasibility of implementation of the solutions provided by the computer model. This chapter also presents the verification of the solutions, through computer simulation, in terms of the reduction of the time to complete a field work. Chapter 5 discusses and compares the effective field capacity and field efficiency when a single large machine is replaced with two or three smaller ones, contingent upon performing the operation under the same conditions. Chapter 6 concludes major findings from the present research and discusses the future work.

The research presented in this dissertation has been accepted or submitted for publication in the following peer-reviewed journals:

1. Seyyedhasani, H., & Dvorak, J. S. (2017). Using the Vehicle Routing Problem to reduce field completion times with multiple machines. *Computers and Electronics in Agriculture*, *134*, 142-150. (Chapter 2)
2. Seyyedhasani, H., & Dvorak, J. S. (2017). Reducing Field Work Time Using Fleet Routing Optimization. *Biosystems Engineering*, Under Review. (Chapter 4)

CHAPTER 2: OBJECTIVE 1: USING THE VEHICLE ROUTING PROBLEM TO REDUCE FIELD COMPLETION TIMES WITH MULTIPLE MACHINES

2.1 SUMMARY

The Vehicle Routing Problem (VRP) is a powerful tool used to express many logistics problems, yet unlike other vehicle routing challenges, agricultural field work consists of machine paths that completely cover a field. In this work, the allocation and ordering of field paths among a number of available machines has been transformed into a VRP that enables optimization of completion time for the entire field. A basic heuristic algorithm (a modified form of the common Clarke-Wright algorithm) and a meta-heuristic algorithm, Tabu Search, were employed for optimization. Both techniques were evaluated through computer simulations in two fields: a hypothetical basic rectangular field and a more complex, real-world field. Field completion times and effective field capacity were calculated for cases when 1, 2, 3, 5, and 10 vehicles were used simultaneously. Although the Tabu Search method required more than two hours to produce its solution on an Intel i7 processor compared to less than one second for the method based on Clarke-Wright, Tabu Search provided better solutions that resulted in reduced field completion times and increased effective field capacity. The benefit provided by Tabu Search was larger in the more complex field and as the number of vehicles increased. With ten vehicles in the real-world field, the benefit provided by Tabu Search over the Modified Clarke-Wright resulted in reduced completion time of 32%, but even with only three vehicles a 15% reduction was obtained. While ten vehicles may only be applicable with future autonomous machines, simultaneous usage of three machines is not uncommon in current production. As producers consider using multiple machines to improve field completion times and effective field capacity, optimization of the vehicle routing will play an important role in ensuring those improvements are fully realized.

2.2 INTRODUCTION

Reducing field completion times is one of the most important factors for producers when making agricultural machinery decisions. It is especially important in operations such as planting, swathing or baling where producers want to minimize temporal differences between crop states in the same field. Weather is brutally unforgiving and the profit penalties for missing the optimal times to perform field operations is frequently severe. Reducing time to finish a field also enables producers to quickly move equipment to the next field and work more acres in limited timeframes. Field completion time reduction requires improving effective field capacity (American Society of Agricultural and Biological Engineers, 2011), and there are two ways to increase effective field capacity – increase the speed, width, or size of individual machines; or use more machines at one time.

Increasing speed or width of machines is a frequently used approach to improving effective field capacity as evidenced by the increasing size and horsepower of agricultural machinery over the decades (Shearer et al., 2010a). In addition to making these machines larger and faster, much research has focused on improving their efficiency by discovering algorithms that divide a field into paths in such a way to minimize turning and other non-productive time (D. D. Bochtis & Vougioukas, 2008; I. A. Hameed, D. D. Bochtis, C. G. Sørensen, & M. Nøremark, 2010; Jin & Tang, 2010; Oksanen & Visala, 2009; Palmer, Wild, & Runtz, 2003; Spekken & de Bruin, 2013). Although larger and faster machines significantly improve capacity, they also cause compaction (Blackmore et al., 2002; Hamza & Anderson, 2005). Researchers have even explored routing optimization for vehicles to specifically reduce compaction potential (Dionysis D. Bochtis, Sørensen, & Green, 2012).

Using multiple machines allows the use of smaller machines with less compaction risk. It also provides redundancy in the event of an equipment failure and more flexibility in machinery management. The use of multiple machines creates several challenges, which researchers have been working to overcome. Operating multiple vehicles in the same area can lead to collisions, which S. G. Vougioukas (2012) addressed through the use of peer-to-peer and master-slave control of navigation functions. When developing a team of peat harvesting autonomous tractors, Johnson, Naffin, Puhalla, Sanchez, and Wellington (2009) allocated work by assigning vehicles to separate works zones and prevented collisions in shared common areas by limiting access to these areas to only one vehicle at a time. The control systems of agricultural robots designed to operate in fleets have been developed through multi-agent-simulation (Arguenon, Bergues-Lagarde, Rosenberger, Bro, & Smari, 2006) and three dimensional environment modelling (Emmi, Paredes-Madrid, Ribeiro, Pajares, & Gonzalez-de-Santos, 2013). When using multiple machines together in a field, it is vital to properly allocate work to machines and coordinate their actions so they efficiently finish their tasks.

Computer scientists, operations management specialists and others researching logistics have long realized the importance of efficient routing of multiple vehicles. The classical Vehicle Routing Problem (VRP) was first devised in 1959 to route fleets of fuel trucks to customers (Dantzig & Ramser, 1959). In applying the VRP, each customer is transformed into a node in a network graph and travel costs are assigned to the connections between the nodes. The VRP then provides a set of constraints that requires that in any solution all customers must be visited by at least one vehicle that has capacity to service that customer, and that vehicles start and end positions in designated locations (Toth & Vigo, 2002). Many variations of the VRP exist which add constraints for delivery order, or time windows for certain deliveries. Some constraints, such as the capacity constraint can also be relaxed. This relaxation provides a representation often called the Multiple Traveling Salesperson Problem (m-TSP). Careful consideration must be made of the optimization function and the travel cost assignment when setting up the VRP. One common goal is to minimize the total travel time of all vehicles so costs are expressed as time, while other goals include minimizing fuel usage or distance traveled. This method of casting the routing problem as a mathematical optimization problem has proven a powerful tool to improve logistics from maintenance service calls (Toth & Vigo, 2002) to agricultural field applications (D. D. Bochtis & Sørensen, 2009; Conesa-Muñoz, Pajares, & Ribeiro, 2016).

When applying the VRP to agricultural field applications, the challenge becomes transforming an area coverage problem into a VRP with nodes, a cost matrix and an optimization function. D. D. Bochtis and Sørensen (2009) proposed a method to minimize non-productive time in a field that had already been divided into paths by assigning nodes at each path endpoint and costs between the nodes based on non-productive time. Although this method requires that the field already be broken into paths, this is easily achievable using available path creation algorithms. Alternatively, many agricultural operations must be performed on already pre-established paths (e.g. baling, spraying on tramlines, spraying by row in growing crops, or any operation in controlled traffic farming). The Bochtis and Sørensen transformation would be excellent for routing a single vehicle on these pre-established paths or for multiple vehicles when machine efficiency is more important than field completion times (such as when the field is located adjacent to equipment storage). Unfortunately, minimizing non-productive time is not the same as minimizing the time necessary to complete a field. It is often the case that increasing the number of vehicles increases non-productive time. This is because extra time must be spent traveling past paths assigned to other vehicles. A different transformation must be used to solve for the minimum time to complete a field.

Although the VRP has been the subject of research by computer scientists for decades, the problem is computationally intractable (Toth & Vigo, 2002). Therefore, solutions to VRP must rely on heuristics that produce good solutions rather than finding a single optimum answer. One of the earliest and most popular heuristics is the Clarke-Wright Savings Algorithm (Clarke & Wright, 1964). This algorithm produces reasonable solutions quickly (Toth & Vigo, 2002) but always optimizes for minimum total travel time and uses vehicle capacity limits to determine how many vehicles to use. Clarke-Wright has been implemented for single vehicle route optimization in agricultural field work by several researchers (Dionysis D. Bochtis, Sørensen, Busato, & Berruto, 2013; Spekken & de Bruin, 2013). Recently more advanced meta-heuristics have been developed that can provide more optimal solutions and utilize other optimization functions. Long-term scheduling of agricultural field work has been optimized using a two-phase metaheuristic based on simulated annealing, genetic algorithms and hybrid Petri nets (Guan, Nakamura, Shikanai, & Okazaki, 2009). Unfortunately, the most popular meta-heuristics, such as neural networks or genetic algorithms, are not efficient at exploring the solution space posed by the VRP (Toth & Vigo, 2002). Nevertheless, researchers have successfully applied modified versions of genetic algorithms for routing of vehicles in agricultural fields (Alba & Dorronsoro, 2004; I. A. Hameed, Bochtis, & Sørensen, 2011) and controlling robots in greenhouses (Komasilovs, Stalidzans, Osadcuks, & Mednis, 2013). However, for VRP, Tabu Search has been identified as much more efficient at identifying solutions to the VRP (Toth & Vigo, 2002).

The goal of this project was to develop a computerized method for path assignment among a fleet of farm machinery in a field that minimized the time to complete a field. The field paths considered are already defined, either by an algorithm that optimally decomposes a field into paths or by the nature of the field operation. Although the VRP is designed to work with vehicles with capacity restraints, in this initial investigation we relaxed the capacity requirement and focused on operations like tillage, swathing, baling, some seeding, and some fertilizing application where the capacity restraints are either nonexistent or inconsequential. The objectives of this project to meet the goal are: 1) transform the multiple vehicle field path assignment problem into a VRP that allows minimization of field completion time; 2) establish techniques that produce solutions to the developed VRP transformation; and 3) compare the techniques based on their ability to reduce completion times.

2.3 MATERIALS AND METHODS

The allocation problem began with a set of travel paths in a field along which the agricultural vehicle was required to drive. These paths were represented by the location coordinates of their endpoints. The number of vehicles and their travel characteristics including speed and turning ability must also be known. Several steps were required to take this basic information and turn it into efficiently allocated routings for multiple vehicles. The first step was to turn the vehicle information and location coordinates into a mathematical representation based on nodes and travel costs. The results of this first stage are a cost matrix (for optimization) and a transformation matrix (to relate nodes to physical field locations). The next step is to apply an optimization algorithm to search the solution space provided by the mathematical representation of the problem. A variety of optimization algorithms can be used, but the result will be a list of nodes representing the route for each vehicle. The final stage of this process is to convert the routes from a list of nodes into physical locations and waypoints to control actual vehicle travel. In the final stage, completion time, machine operation time, machine efficiency and whether the routes are valid are calculated. In this project, all of these stages of the routing process were implemented in MATLAB code. Each stage provides its own outputs which are then used as the inputs to the subsequent stage.

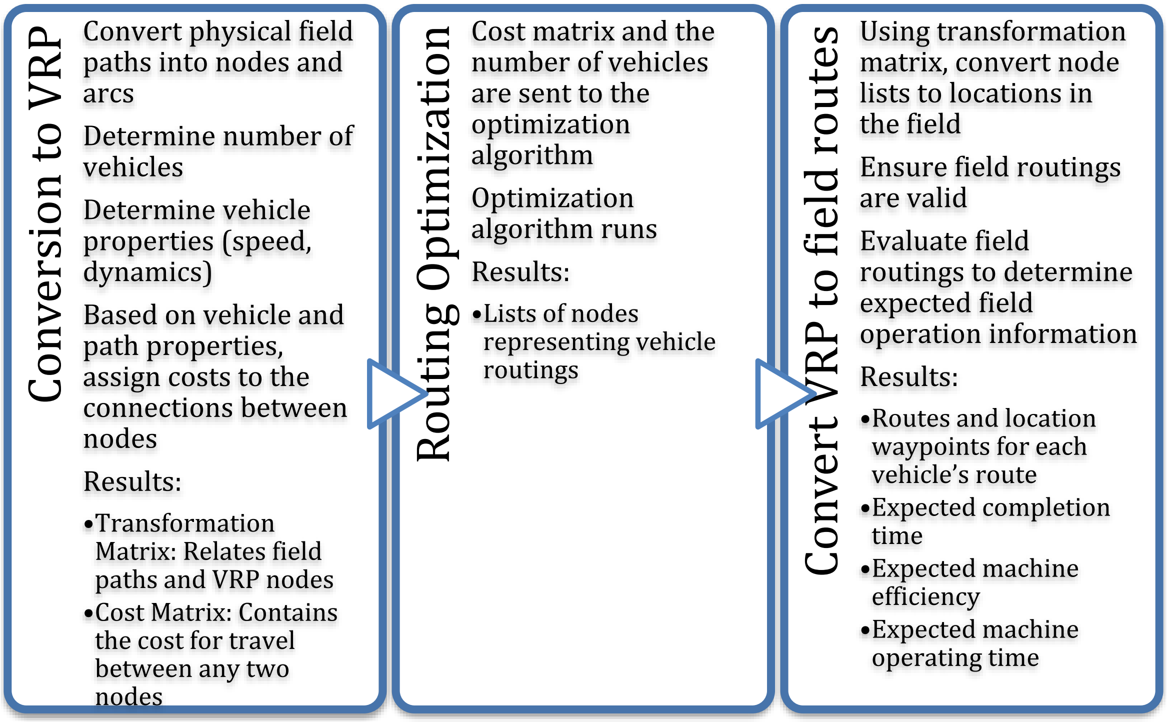


Figure 2-1. Steps in the field path allocation and route creation process.

2.3.1 VRP Conversion

A VRP is expressed as a network graph with a set of arcs, E, connecting a set of nodes, N, to each other. A cost, c_{ab}, is associated with each arc and represents the cost of travel between the nodes a and b connected by that arc.

The first step in conversion to a VRP from a field path representation is node assignment. The initial agricultural field work problem consists of a list of vehicle paths to be worked. Each path is defined by its two end points (Figure 2-2a). In this project, the paths were converted into VRP representation using 3 nodes per path. Each endpoint was mapped to a VRP node and an extra node was added at the midpoint of the path (Figure 2-2b).

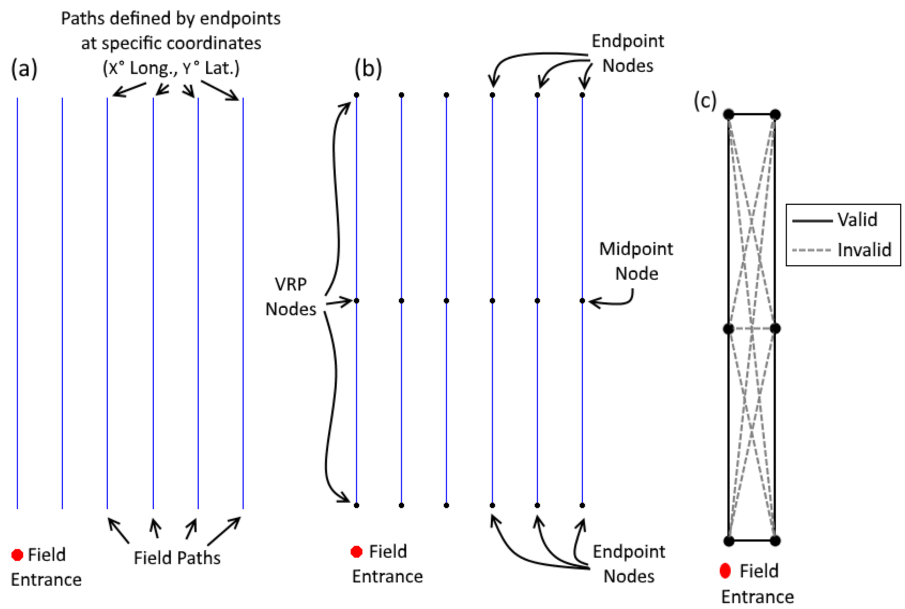


Figure 2-2. Field with (a) paths to be worked by a vehicle, (b) with the VRP nodes assigned to those paths, and (c) invalid and valid arcs for travel (represented for only two paths).

The next step in the conversion process is the assignment of costs to the arcs between nodes. The method of cost assignment in VRPs varies based on the optimization criterion, but in this case, simple travel time was the desired variable. For the connections between an endpoint and the midpoint on the same path, the cost of that arc was assigned as travel time for the vehicle to go from the endpoint to the midpoint of the path. Likewise, the cost between endpoints connected to the same headland in the field was assigned to be the travel time for a vehicle to travel from one path to the other. Arcs between all other nodes were considered invalid for vehicle travel (Figure 2-2c), and therefore, the costs on these connections were set to a value at least ten times greater than the cost on any valid path to significantly penalize solutions that use invalid arcs. For each midpoint, the only feasible arcs for travel were those connected to the endpoints of the same path.

This three-node per path structure differs from the previously published two-node structure by D. D. Bochtis and Sørensen (2009). Their two-node structure relied on a cost of zero on the arc between the nodes representing the endpoints of the path to force the solution to include travel down every field path. This cost structure enabled optimizing based on minimization of non-working time, but it does not permit optimizations that consider actual travel time. In our transformation, the third node at the midpoint of the path enforces travel down every path since the only valid connection to and from this node is from each endpoint. While adding a third node increases the size of the matrices involved in solving the VRP, it enables direct consideration of travel times in the optimization.

The solution to this VRP is a route, R_j, for each vehicle, V_j, in the set of available vehicles, V, and takes the form of permutation sets of $R_j = \langle i_1, i_2, \dots, i_{|R_j|} \rangle$ where each i represents a node visited by the vehicle. The governing constraints for this problem are:

(1) Each route starts and ends at the same location (In VRP notation, the depot and node 0, $i = 0$), i.e., $i_1 = i_{|R_j|} = 0$, and $\left\{i_2, \dots, i_{|R_j|-1}\right\} \subseteq N \setminus \{0\}$, and

(2) Each node is visited by exactly one vehicle, i.e., $\bigcap_{j=1}^{|V|} R_j = 0 \wedge \bigcup_{j=1}^{|V|} R_j = N$.

There are alternative notations for expressing the VRP (Toth & Vigo, 2002), but for consistency with publications in agricultural machinery we have adopted D. D. Bochtis and Sørensen (2009) notation. D. D. Bochtis and Sørensen (2009) also gives a more in-depth consideration of the variables and equations.

The final VRP conversion step was the creation of a fitness function that appropriately captures the optimization criteria of the problem. In most VRPs, the variable of primary concern is the sum of all vehicles' travel costs,

(1.1)

$$cost_{all} = \sum_{a \in N} \sum_{b \in N} c_{ab} x_{ab}$$

where x_{ab} is 1 if a route, R_j, in the solution set contains a connection between nodes *a* and *b* (represented by *a* and *b* appearing consecutively in R_j) and 0 otherwise. The traditional goal is minimization of this cost, $min(cost_{all})$.

The above fitness function reduces the total cost of the solution. However, when the focus is shifted to when all vehicles are finished, the variable of concern becomes only the vehicle with the highest travel time or cost as it would be the last to finish:

(1.2)

$$cost_{last} = max_{j | j \in V} \left(\sum_{a \in N} \sum_{b \in N} c_{ab} x_{abj} \right)$$

where x_{abj} is 1 if the route, R_j, for vehicle j in the solution set contains a connection between nodes a and b (represented by a and b appearing consecutively in R_j) and 0 otherwise. The added variable, j, allows calculating each route individually.

Although farmers will be primarily interested in maximizing field capacity and finishing the field as quickly as possible, simply using equation (1.3) for optimization is not suitable. It only considers the travel time of the last vehicle to finish and ignores any optimization of other vehicles. This hinders the optimization process as solution improvements will only be accepted if they help the last vehicle to finish, and improvements to other vehicles will be ignored. To improve optimization, a better fitness function for this problem is one that considers both the total time for all vehicles and the time for the last vehicle to finish:

(1.3)

$$\min\left(z\, cost_{last} + (1-z)\frac{cost_{all}}{|V|}\right), z|0 \le z \le 1$$

where z represents the focus placed on optimizing total travel time versus field completion time.

Utilizing a weighting function enables adjusting the focus of the optimization for producers who may also want a balance between total machine time and field completion time. To ensure the weighting variable appropriately reflects the percentage of focus on each part of the equation, the total travel time, $cost_{all}$, is divided by the number of vehicles used. In this project, the primary focus was on minimizing field completion time. In initial testing, a weighting value of 0.80 was found to provide sufficient optimization for all vehicles while still selecting solutions that minimized time to field completion.

2.4 VRP Solution Methods

2.4.1 Modified Clarke-Wright

The Clarke-Wright Savings Algorithm (Clarke & Wright, 1964) is a cost savings algorithm that attempts to reduce the combined cost of the travel paths of all vehicles. While this algorithm almost never produces an optimal solution, its calculations can be performed quickly and it usually produces a reasonably acceptable solution (Toth &

Vigo, 2002). Without capacity restraints, it generally links all nodes into a path for a single vehicle.

Because the agricultural tasks considered in this project are non-capacity limited and the optimization goal is not reducing total costs, direct application of the Clarke-Wright Savings algorithm is inappropriate. When the base Clarke-Wright algorithm is applied to the VRP representations in this work, a single long route always appeared (Figure 2-3). This route did not meet the established optimization criteria, yet it required limited processing time. For a single vehicle, this route did represent a reasonable path.

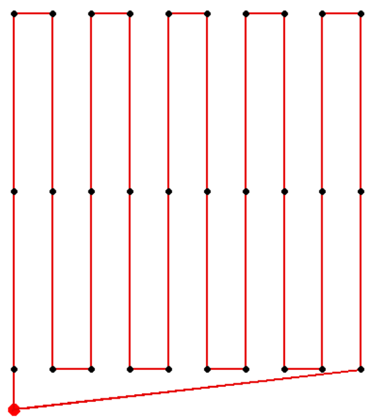


Figure 2-3. Initial Clarke-Wright Solution showing a single long route.

To produce a solution for our multiple vehicle problem, the single vehicle Clarke-Wright path was divided to produce one segment for each available vehicle. Initially these segments were of equal length, but these became unequal when the travel times to and from the starting point were added. This blind segmentation also resulted in poor decisions like starting a route on the far headland rather than the close headland. To address both of these issues, these breaking points of the initial path chain were then shifted one node by one node, and alterations were accepted if they reduced the cost of the fitness function. The result represented a solution for this class of agricultural field work problems based on a modified version of the Clark-Wright Savings Algorithm (Figure 2-4).

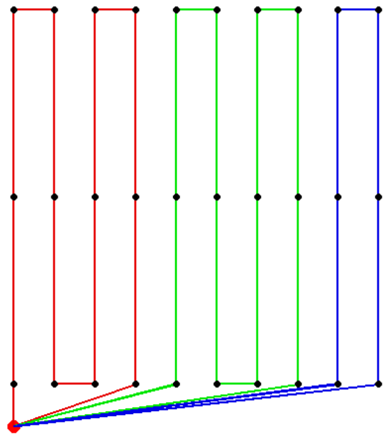


Figure 2-4. Modified Clarke-Wright Solution showing route broken into paths for three vehicles.

The code to implement the Modified Clarke-Wright optimization was written as a function in MATLAB. The computation began with the necessary steps to perform the cost savings calculations and route simplification procedures that are provided by the Clarke-Wright algorithm. The result of this process was a single long route for one vehicle. The next step in the code was to identify appropriate locations at which to divide this single long chain of paths for multiple vehicles. The Modified Clarke-Wright code did contain several iterations and code loops to sort cost savings or to determine route division locations, but these were limited. A single pass through the entire Modified Clarke-Wright procedure provided the final result from the algorithm which reduced the time needed to produce a result compared to other methods.

2.4.2 Tabu Search

Tabu Search is a high-level meta-heuristic procedure developed by Glover (1989). As with other meta-heuristics, like neural networks or genetic algorithms, there are many implementations for Tabu Search. However, the primary feature of all Tabu Search algorithms is a list of Tabu improvement operations that the algorithm has already tried and is forbidden to utilize in future iterations. This Tabu list forces the optimization procedure to search more widely for solutions and prevents trapping at a local minimum of the optimization function.

The Tabu Search algorithm used in this study utilized three operations: swap, insertion and inversion. It considered all eligible combinations of these operations at every iteration of the algorithm. The Tabu Search had to begin its iteration process with an initial solution. Therefore, the solution provided by the Modified Clarke-Wright algorithm was used.

The Tabu Search algorithm was also implemented in MATLAB. The Tabu Search is a complicated algorithm, and as such required hundreds of lines of code and many functions to create. First, the algorithm determined all possible actions involving the swap, insertion and inversion of nodes to create an action list as a cell array. Using this array, the algorithm then applied each of these actions in an attempt to improve the solution. Tabu Search accepted the action if it improved the fitness of the solution and marked that same action as tabu in future iterations. This was to discourage the search from repeating the move of the immediately previous action to avoid becoming stuck in suboptimal regions. The tabu action would be released for use after the number of subsequent movements was equal to half of the number of total possible actions. The algorithm checked every action and identified the best permissible and best forbidden action. The best permissible action was accepted unless the forbidden action was better than any currently known best solution. Finally, a new solution was generated. This procedure was repeated with continuously improving solutions until 300 iterations had passed with no improvement. At this point, the algorithm halted and provided its best solution as the optimized paths. In preliminary experiments, the total number of iterations was usually between 600 and 700.

2.4.3 Test Conditions

The VRP transformation and the solution techniques were tested in two fields. One was a hypothetical basic rectangular field while the other was based on a non-convex real-world field that has been used in other agricultural field path optimization papers. The basic field was a simple rectangle with a worked area of 13.2 ha. Paths were created parallel to the short side of the field. Although not the most efficient path direction, the focus in this artificial field was merely to create a field with many parallel paths upon which to distribute the vehicles. The field was divided into paths with an implement width of 10 m resulting in 90 straight paths surrounded by two border passes in the headlands for a total of 98 paths (Figure 2-5). The total path length was 13,200 m with the longest path at 930 m.

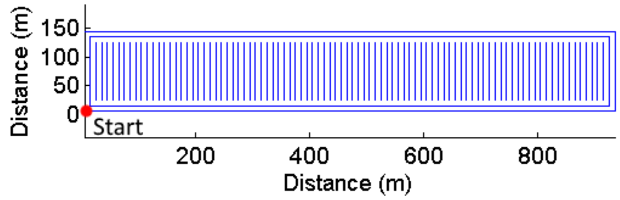


Figure 2-5. Hypothetical basic rectangular field

The second field was a non-convex field based on a real world field example consisting of 88 paths (Figure 2-6). The paths in this field were provided as an example of optimal path direction in the path creation research by I. A. Hameed et al. (2011). The scale of this field was adjusted to correspond with the same 10 m implement width used in the rectangular field. This resulted in a total path length of 18,377 m with the longest path of 707 m and an overall area to work of 18.3 ha. An initial starting point for all vehicles was selected and marked as "start." The field boundary and the intruding area in the non-convex shape were considered passible, as would be the case if this land also belonged to the same farmer and its current use would not be significantly impacted by limited cross traffic. The non-convex shape meant that a direct connection between field path endpoints on the same side of the field could require driving across other non-headland field paths. This travel was permitted in this investigation, as would be the case for operations like planting. In other applications, such as spraying in growing row crops, driving across rows would be unacceptable, and the cost matrix would need to be adjusted to either disallow that connection or include the time to drive to and along the headland.

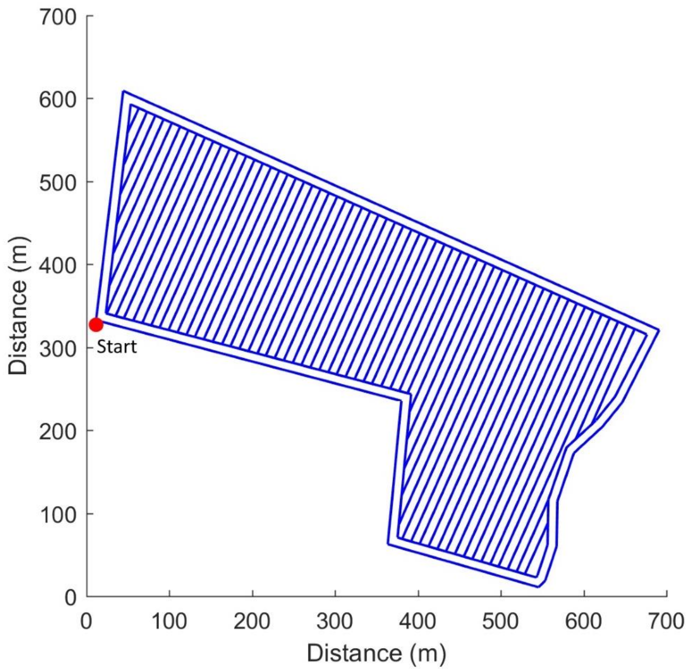


Figure 2-6. Non-convex field

In a final application, the cost matrix would be created based on the travel times expected between each point based on operating speeds and handling characteristics of the individual machines available to perform the fieldwork. For this initial testing phase, the simulation model was simplified to constant speed vehicles capable of instant turns (massless and holonomic steering) traveling at 2 m s^{-1}. The cost matrix was then created based on the travel times between the locations of each node in the field.

To investigate if these methods could produce useful information and identify the strengths of different routings, each algorithm (Modified Clark-Wright and Tabu Search), was tested in each field with 1, 2, 3, 5, and 10 vehicles. Each solution was checked to determine whether the generated solution was feasible. The vehicle paths, the total combined operating time of all vehicles, and the operating time of the single vehicle that operated for the longest period of time was recorded.

2.5 RESULTS

2.5.1 VRP Transformation

The VRP transformation of the test fields resulted in the node placements as shown in Figure 9a for the basic field and 9b for the non-convex field.

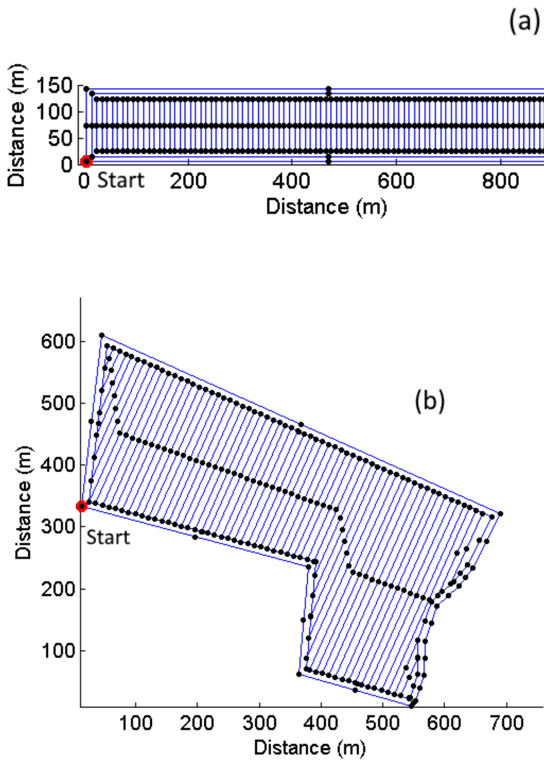


Figure 2-7. The (a) basic and (b) non-convex fields with VRP nodes on field paths.

In the cost matrix, there are only two feasible connections to each middle node and they are from the endpoints of the path. Since the VRP requires that each node be visited once and only once, the middle node on each field path creates a situation where each path must be traversed.

The end result of the VRP transformation is a list of nodes representing the paths in the field and a cost matrix showing the cost of travel on the arcs between any two nodes. These arcs can be divided into several categories (Table 2-1). For both fields, 77% of the total arcs are infeasible and unacceptable in any realistic solution. There are also a large number of arcs that may be used in feasible solutions. Finally, there are a small number of arcs that must be included. These required arcs represent the original work paths in the field.

Table 2-1. Properties of the basic rectangular field and a non-convex field after VRP transformation

Properties	Field Name	
	Basic Field	Non-convex Field
Nodes	294	264
Required Arcs	196	176
Available Infeasible Arcs	66934	53944
Available Feasible Arcs	19780	15992

The high number of infeasible arcs complicated the solution space and limited solution methods as those that attempt random selections would mostly select infeasible arcs. However, the normal constraints within the VRP already make it difficult to solve with such methods so this limitation was not too severe. More importantly, this VRP transformation did create a representation that enabled assigning travel times to every path in the field while still ensuring all fieldwork paths are traversed.

2.5.2 Solution Methods

Both the Modified Clarke-Wright Savings Algorithm and Tabu Search always generated solutions containing only feasible arcs and included all required arcs. Figure 2-8 shows a representative example of the solutions generated by each of these techniques. The displayed solutions are for the non-convex field with five vehicles. As expected, the Modified Clarke-Wright method assigned paths to each vehicle that are closely grouped to each other since its solution is obtained by dividing a single long chain of paths. This resulted in three vehicles (represented by purple, blue and yellow) that had to travel to the far end of the field to start or finish working. The Modified Clarke-Wright method produced a solution not unlike that used by many producers today, where one vehicle sets an A-B line and provides the coordinates to the other vehicles. The drivers then try to divide the field evenly and drive to their sections, which they will work until they meet the work performed by the other drivers. The Tabu Search eliminated more of the inefficient non-working travel time and utilized the border passes in the headlands to distribute vehicles to the far side of the field. Also with Tabu Search, vehicles do not always proceed from one path to a contiguous path as redistributing some paths enabled a more even distribution of work and the field to be completed more quickly overall.

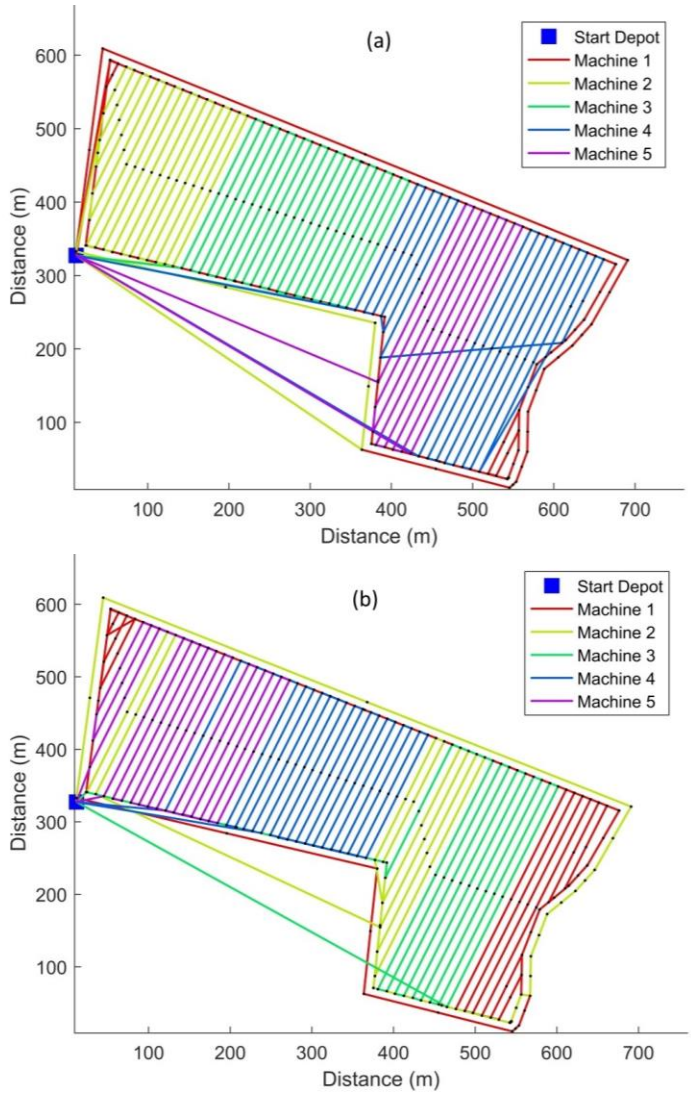


Figure 2-8. Solutions in the non-convex field for 5 vehicles using (a) the Modified Clarke-Wright algorithm and (b) Tabu Search. Each vehicle's travel is represented by a different color line.

One of the biggest differences between the solution methods is the time necessary to generate a solution. The solutions from the Modified Clarke-Wright were calculated so quickly that on modern processers, the solution was generated nearly instantaneously. The Tabu Search was much more computationally expensive. The total run time to generate an acceptable solution was highly variable and depended on field complexity, number of vehicles and the initial solution used to seed the Tabu Search. However, in no case was the Tabu Search algorithm able to complete processing in less than 2 hours on an Intel i7 processor and in some cases required several more hours to complete.

2.5.3 Field Completion Times

2.5.3.1 Basic Rectangular Field

As Figure 2-9 illustrates, the time required to complete the field was identical for both the Modified Clarke-Wright (MCW in figures 9-12) and Tabu Search (TS in figures 9-12) methods when only using one or two vehicles. However, there is a significant difference in the completion time as more vehicles are used. With ten vehicles, the routing provided by Tabu Search would complete the field in 26% less time.

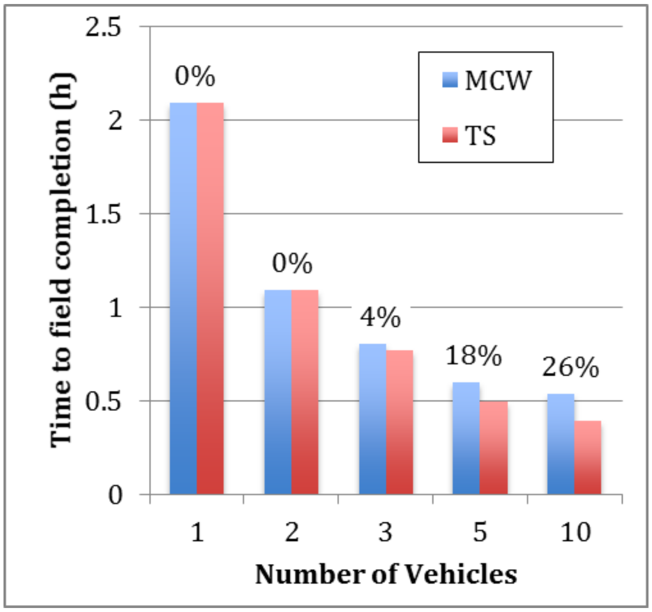


Figure 2-9. Comparison of field completion time in the basic rectangular field (percent decrease from Modified Clarke-Wright (MCW) to Tabu Search (TS) shown above columns).

Effective field capacity, the total area worked divided by the time until the field was complete, provides another way to look at the results. When viewed this way (Figure 2-10), it becomes apparent that effective field capacity did not scale perfectly with the number of vehicles. With additional vehicles, the routing increased in complexity and some efficiency was lost. With one vehicle, effective field capacity was 6.3 ha h^{-1}, and with two vehicles it was almost doubled to 12.1 ha h^{-1} (6.0 ha h^{-1}per vehicle). However with ten vehicles, the highest effective field capacity (from Tabu Search) was only 3.4 ha h^{-1} per vehicle, which is only 53% of the original field capacity per vehicle.

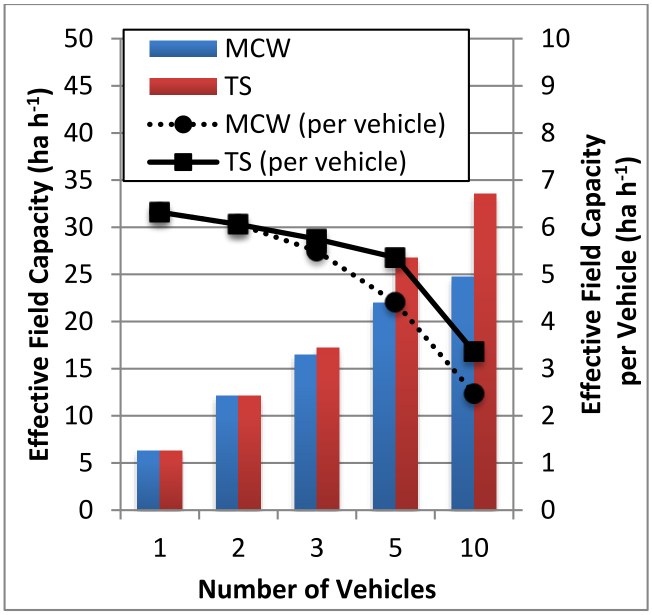


Figure 2-10. Effective field capacity (both total and per vehicle) in the basic field.

2.5.3.2 Non-Convex Field

For the non-convex field, the Tabu Search technique always reduced the completion time and provided a better solution than Modified Clarke-Wright (Figure 2-11). In contrast, in the basic field, Tabu Search was unable to improve on the Modified Clarke-Wright solution when only one or two vehicles were used. In the non-convex field, the magnitude of the improvement provided by the Tabu Search algorithm over the Modified Clarke-Wright method was also greater for every number of vehicles tested. Even when employing only three vehicles, using Tabu Search reduced completion time by a non-trivial 15% in the non-convex field compared to a difference of only 4% in the basic rectangular field. The Modified Clarke-Wright routings were not unreasonable as was previously shown in Figure 10 with 5 vehicles, but the difference in completion times between the solutions shown in Figure 10a and Figure 10b is 21% (the 5 vehicle point in Figure 13).

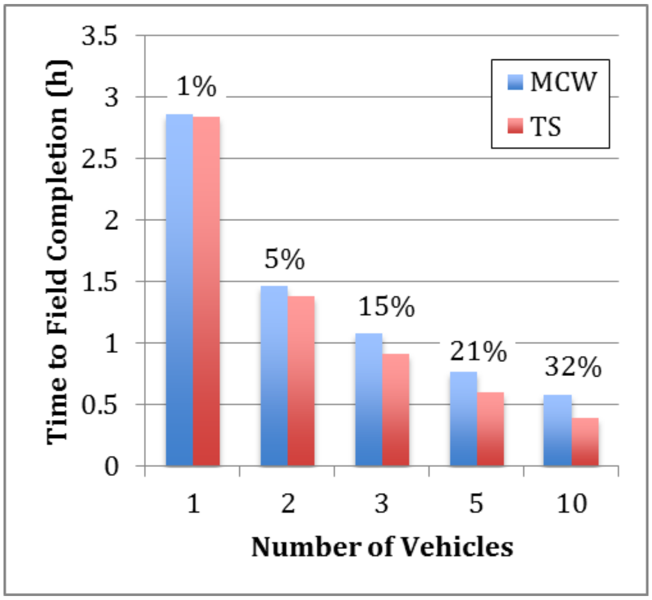


Figure 2-11. Comparison of field completion time in the non-convex field (percent decrease from Modified Clarke-Wright (MCW) to Tabu Search (TS) shown above columns).

Interestingly, Tabu Search in this irregular field was able to *improve* effective field capacity per vehicle in some cases as the number of vehicles increased (Figure 2-12). With Tabu Search, the effective field capacity improved from 6.47 ha h^{-1} with one vehicle to 6.63 ha h^{-1} with two vehicles and to 6.67 ha h^{-1} with three vehicles. There was a loss of efficiency at higher numbers of vehicles, but this decline was not as steep as with the basic field. With Tabu Search and ten vehicles in this field, the capacity per vehicle only dropped to 4.6 ha h^{-1}, or 71% of the single-vehicle effective field capacity compared to the 53% seen in the basic field.

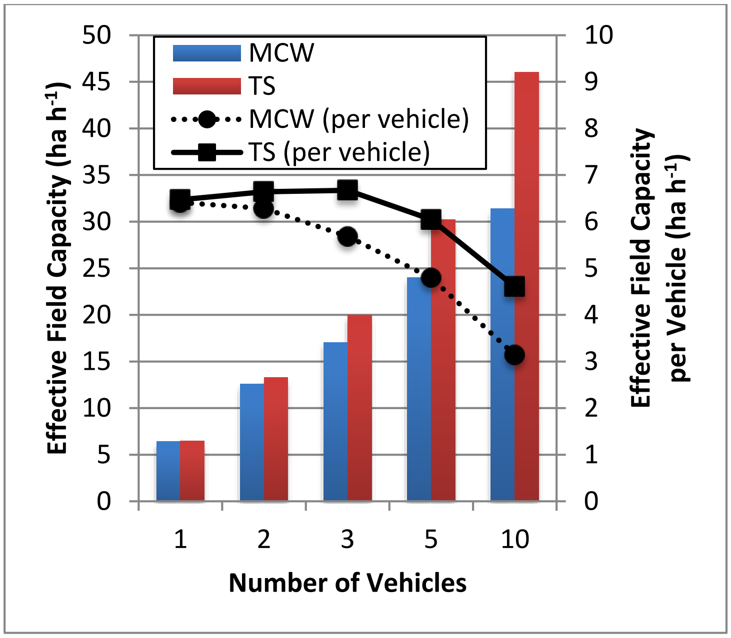


Figure 2-12. Effective field capacity in the non-convex field.

2.6 DISCUSSION

In even moderately complex fields like the non-convex one used in this study, there are clear benefits to using a strong optimization method. Tabu Search was able to maintain effective field capacity per vehicle even as the basic Modified Clarke-Wright heuristic always saw declining benefits to adding vehicles. However, utilizing Tabu Search is only possible when the field path allocation and routing problem has been converted into a more standard mathematical representation.

The results of this work are directly applicable to current production practices where the navigation computers in machines working together in a field could direct each vehicle driver to follow the path sequence that results in the field being completed in the shortest amount of time. If the field is irregular as in the non-convex field studied here, this optimization could even enable the producer to realize an improvement in effective field capacity with these limited number of vehicles. This would represent a clear improvement over the basic sharing of A-B lines producers now use to coordinate field work.

These results could also find use in the fleets of smaller autonomous vehicles proposed by several researchers (Blackmore et al., 2002; Pitla, Luck, & Shearer, 2010; Shearer et al., 2010a). Almost assuredly, these smaller autonomous vehicles will be transported from field to field on a truck together. Therefore, the overall field capacity will be directly related to the time for the last vehicle to complete its routing. Often, these fleets are envisioned as having more than two or three vehicles, and as this research shows, routing algorithms become very important as the number of vehicles increases toward five or ten vehicles working together in a field.

One strength of the VRP is that the optimization is performed based on the costs contained in the cost matrix. In this initial investigation, the cost matrix was simply assigned based on travel time and assuming all vehicles were identical and traveled at constant speed. In an on-farm implementation, the working speeds, non-working speeds and turning speeds for various types of turns for specific vehicle and implement combinations would be used for costs to provide exact estimates of field completion times. Costs could also vary to reflect the effect on working speed of changes in field conditions like regions with tougher soil or changes in operating conditions, such as slowing down to increase planting precision in regions with high planting density. The VRP can also be implemented with individual cost matrices for each vehicle to enable consideration of heterogeneous vehicles with a variety of handling characteristics as long as they operated on the same paths.

In further work, the model could be improved by tuning it for specific vehicles with actual travel time information from real-world applications. Naturally, there would also be useful work in comparing current farmer path allocation techniques recorded from field data with the routings provided by the optimization algorithm. Finally, agricultural fields are not static and completely predictable before starting field work. The VRP can be represented with stochastic costs in the cost matrix to express this uncertainty (Toth & Vigo, 2002). There could also be value in real-time recalculation of the vehicle routings as the effects of deviations from the expected progress of the vehicles begin to compile. All of these opportunities provide natural extensions of this work now that the basic method has been established here.

2.7 CONCLUSION

The VRP is a valuable tool for optimizing path allocation to finish fields as quickly as possible with multiple vehicles. As this study shows, the standard field work problem can be transformed into a VRP in a manner that enables optimization based on criteria important to farmers. The field path to VRP transformation provided in this project represents each required field work path with three nodes and defines certain arcs between nodes as infeasible to prevent inappropriate vehicle routing. For the fields in this study, this resulted in a cost matrix in which 77% of the arcs were infeasible and marked as so through very high costs. For feasible routes, the cost matrix contained costs based on travelling time and distance between every two nodes.

This VRP representation of the field work routing problem was optimizable through the use of a modified version of the Clarke-Wright algorithm and a Tabu Search algorithm. Most importantly, both techniques always provided feasible solutions. However, there were significant differences in processing time and the level of optimization each provided. Calculation times for a single scenario with Tabu Search required two hours on an Intel i7 processor, while the Modified Clarke-Wright method provided its solution in less than a second. In very basic field routing situations (e.g. routing only one vehicle in either field or two vehicles in the rectangular field), the difference between Modified Clarke-Wright and Tabu Search was less than 1%. However, with the more complex scenarios presented when routing greater numbers of vehicles, Tabu Search provided much better optimization with route completion times of 4% to 32% less than the routes provided by the Modified Clark-Wright method. The routing characteristics from each method are also different. The Modified Clarke-Wright method provided solutions similar to the Work Zone approach currently utilized by many producers. The Tabu Search routes appeared more random, less predictable, and unlike any current routing producers would use. For basic scenarios involving one or a very limited number of vehicles on simple field shapes, a modified version of the Clarke-Wright algorithm was perfectly acceptable. However, as the number of vehicles or field complexity increases, the more powerful Tabu Search algorithm will be necessary for proper optimization.

CHAPTER 3: OBJECTIVE 2: DYNAMIC RE-ROUTING OF A FLEET OF VEHICLES IN AGRICULTURAL OPERATIONS USING THE VEHICLE ROUTING PROBLEM

3.1 SUMMARY

Agricultural field work operations rely on proper machinery management to be successful. Agricultural field work and the machinery operating in them are dynamic, complex entities and producers are often subject to deviations from initial plans as the work proceeds. Therefore, resetting of the paths allocated and scheduled for each vehicle would be needed, due to either unexpected field conditions or machinery management challenges. The goal of this project was to develop a method for applying the VRP that enables dynamic recalculation of the routes. To that end, a combination of Dynamic VRP and Multi-Depot VRP was employed. The solutions were generated using Tabu Search optimization procedure. This dynamic routing method was then tested in simulations of various, common scenarios that would often require rerouting of vehicles. The results revealed the impact of the new routes is dependent on the specifics of the event that necessitated the rerouting. When a vehicle was added to the fleet working the field, the updating procedure was able to use that vehicle to reduce completion times. For removal of a vehicle, the field completion time increased, but the field efficiency improved for the remaining vehicles. When a vehicle completed more work than expected, the procedure enabled the producer to capture this benefit to complete the field in less time; the field efficiency also effectively remained within 3% of the original field efficiency. The procedure was excellent at handling increases in the area coverage with total field completion times largely unchanged. However, it was less capable of addressing the challenges presented by a sudden reduction of field area, with the field capacity, field efficiency and completion time moving in a worse direction by approximately 8% each. This work illustrated the possibility to update field routes for a fleet of vehicles during field operations, and as such provided the opportunity to improve field work outcomes based on changing and variable field and work conditions.

3.2 INTRODUCTION

Agricultural field crop operations rely on proper machinery management to be successful. This requires effective utilization of available machinery. An important driver of utilization is ensuring that the routes that vehicles follow in the field are as efficient as possible. This has led to many researchers investigating the efficiency of various path generation methods (D. D. Bochtis & Vougioukas, 2008; I. A. Hameed et al., 2010; Oksanen & Visala, 2009). However, another important driver of machinery utilization efficiency is the order in which these field paths are worked and, in the case of multiple vehicles working together, the allocation of paths between vehicles (Seyyedhasani & Dvorak, 2017).

One method of allocating and ordering the field work paths among available vehicles is to convert this problem of agricultural field routing into a more standard computer science representation such as the Vehicle Routing Problem (VRP) (D. D. Bochtis & Sørensen, 2009; Seyyedhasani & Dvorak, 2017). Although this class of problems is NP-Hard and therefore computationally intractable, the VRP has seen decades of algorithm development in efforts to produce vehicle routes that are closer to optimal (Toth & Vigo, 2002).

A VRP problem can be solved and implemented from two perspectives—static and dynamic. In a static VRP, the solution for the problem is generated in the beginning and the route for each vehicle is determined a priori. In a dynamic VRP, the solution can be redefined in an ongoing fashion as new, unknown inputs are revealed during the execution of the routes (Novoa & Storer, 2009; Secomandi & Margot, 2009). Jaillet and Wagner (2008) referred to this class of VRPs as online routing. A dynamic VRP requires a different mathematical representation than a static VRP as the vehicles are already in motion and parts of the routes have already been completed.

Earlier work applying the VRP for routing of machinery in agricultural fields has focused on the static approach of producing initial routes for the vehicles. However, agricultural fields and the machinery operating in them are dynamic, complex entities and producers are often forced to deviate from initial plans as the work progresses. Unexpected field conditions can cause deviations in work rates of vehicles. Machinery can break down and remove a vehicle from the fleet in a field. A new vehicle could be added to a field fleet. Producers can encounter wet spots or other issues that prevent them from completing certain field sections. At other times, producers may decide to increase the area within a field that is devoted to a certain crop. All of these situations can happen once a field operation is underway. These are referred to as evolution and quality of information, according to Psaraftis (1988), to address the dynamic VRP in the real-world applications. A broadly applicable routing system must be able to generate new routes for the fleet in the event that any of these events occurs.

The goal of this project was to develop a method for applying the VRP that enables dynamic recalculation of the routes. This dynamic routing method was then tested in simulations of various scenarios that would often require rerouting of vehicles. These new routes are evaluated and compared to the original routes to determine the effectiveness of the rerouting procedure in terms of important field machinery management parameters of field capacity, field time, and field efficiency.

3.3 MATERIALS AND METHODS

Updating the path allocation to each vehicle in a fleet working together can be viewed as a variant of the classic VRP. The working paths in the field are transformed into VRP nodes and costs assigned for travel between these nodes. This transformation of the field enables application of VRP solution techniques to produce vehicle routes in the field. The traditional VRP assumes that all vehicles start and stop at the same location. However, when updating routes, start locations will be different for each vehicle, different from the stop locations, and spread out across the field. The Multiple Depot variant of the VRP (MDVRP) was developed for instances in which each vehicle starts and stops from individual depots. In this work, we add a dynamic aspect to the MDVRP, which permits the start and stop depots to be at different locations. Hence, the solution of the problem consists of double-depot routes.

V_j	the vehicle $j \in N$ from the set of available vehicles, i.e., $V_j \in V$
R_j	the permutation set that consists of the numbers and the order of the nodes visited by the vehicle V_j, according to the VRP solution, $R_j = \langle i_1, i_2, \dots, i_{\lvert R_j \rvert} \rangle$
i	the node number allocated to a vehicle, V_j, according to the VRP solution
G	the complete directed graph, $G = (N, E)$
N	the set of nodes in the VRP graph, $N = (N_f \cup N_v \cup N_d)$
N_f	the set of field nodes, $N_f = \{n_1, \dots, n_{\lvert N_f \rvert}\}$
N_v	the set of dynamic depots, $N_v = \{n_{\lvert N_f \rvert+1}, \dots, n_{\lvert N_f \rvert+\lvert N_v \rvert}\}$
N_d	the stop depot, $N_d = n_{\lvert N_f \rvert+\lvert N_v \rvert+1}$
E	the set of the arcs (connections) in the VRP graph, $E = \{(n_a, n_b): n_a, n_b \in N, a \neq b\}$
C	the cost matrix of the graph, $C = \lvert N \rvert \times \lvert N \rvert$
c_{ab}	the travel cost associated with each connection $(n_a, n_b) \in E$
M	the large number to penalize VRP solutions that use invalid connections
x_{ab}	a binary variable, which is 1 if a route, R_j, in the VRP solution includes the connection $(n_a, n_b) \in E$
$cost_{all}$	the sum of the travel cost of vehicles, in the VRP solution
$cost_{last}$	the highest travel cost of vehicles, in the VRP solution
z	the weight parameter, $0 \leq z \leq 1$, for field completion time versus total field work

Abbreviations

VRP	vehicle routing problem
DVRP	dynamic Vehicle routing problem
MDVRP	multi-depot Vehicle routing problem
DMDVRP	dynamic multi-depot Vehicle routing problem
CW	Clarke-Wright
TS	tabu search

Figure 3-1. Nomenclature

3.3.1 DMDVRP conversion

The first step in the representation of DMDVRP is to handle the dynamic part of the problem. To that end, the current location of each vehicle is set as a dynamic depot. Since this optimization is occurring while field work is already underway, the dynamic depots can be situated anywhere in the field. Figure 1 illustrates a representative example in which routes are to be updated when 25% of the field work is completed.

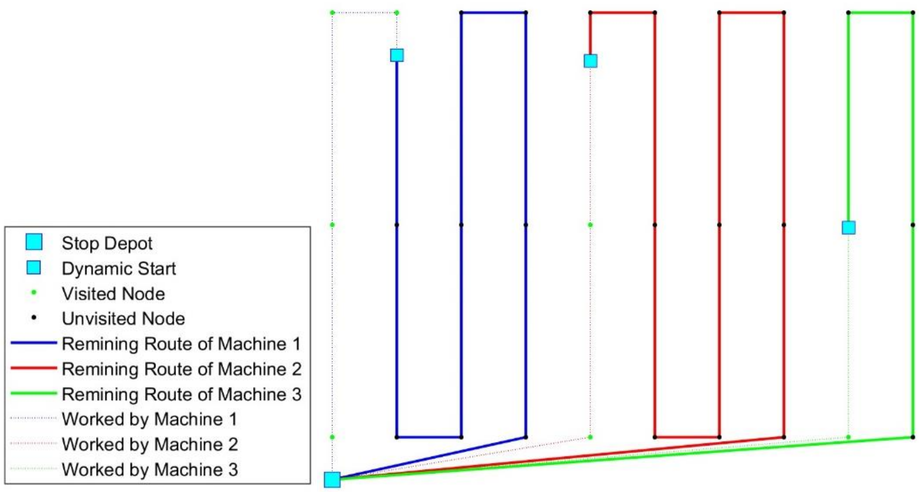


Figure 3-2. Dynamic depots, worked area, and unworked area, and field routes when re-routing in a field that is 25% complete

For vehicles that are currently working on a path, their start depot is moved to the next midpoint or endpoint. This reduces the addition of new nodes and simplifies solution generation since the vehicles must finish their paths. At the end of the route generation process, the travel cost associated with moving the start depot is added back to the vehicle assigned to the start depot. If a vehicle is travelling between paths, its current location is used for the dynamic starting depot as it can proceed in any direction. If the route update is occurring because a vehicle was removed from the fleet, that entire path is considered unworked to force another vehicle to finish the path. Finally, nodes from paths that have already been worked are removed from the list of available nodes.

3.3.2 Node-Representation

The nodes are assigned to the remaining field tracks as shown in Figure 3-3. The pattern of assignment causes the endpoints of tracks to be $\{(3q) \cup (3q+1) | q \in \mathbb{N} \cup \{0\}\}$. Midpoints are represented as $\{(3q) + 2 | q \in \mathbb{N} \cup \{0\}\}$. The dynamic start depots are assigned numbers after the field nodes. The stop depot is assigned the final node number.

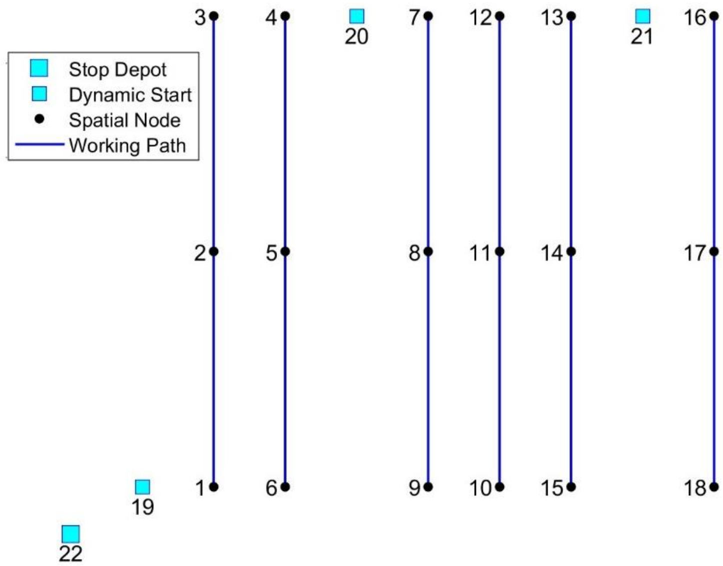


Figure 3-3. Node-representation of the problem

3.3.3 Formulation

The final solution to the DMDVRP is characterized as a route, R_j, for each vehicle, V_j, in the set of available vehicles, V, and takes the form of permutation sets of $R_j = \langle i_1, i_2, \dots, i_{|R_j|} \rangle$ where each *i* represents the node allocated to the vehicle. Therefore, the problem can be formulated as follows. Let *G* = *(N, E)* be a directed graph where $N = (N_f \cup N_v \cup \ N_d)$ as total nodes consists of $N_f = \{n_1, \dots, n_{|N_f|}\}$ as the set of field nodes, $N_v = \{n_{|N_f|+1}, \dots, n_{|N_f|+|N_v|}\}$ as the set of dynamic depots, and $N_d = n_{|N_f|+|N_v|+1}$ as the stop depot, and $E = \{(n_a, n_b): n_a, n_b \in N, a \neq b\}$ is the set of the arcs.

The governing constraints for this problem are:

(1) Each route starts at its associated dynamic depot, i.e., $i_1 \subseteq Nv$, and for a given R_j, $i_1 = Nv_j$,

(2) All routes end at the same location (the stop depot and last node, *i* = n), i.e., $i_{|R_j|} = |N|$,

(3) Each vehicle visits only field nodes, i.e., $\left\{i_2, \dots, i_{|R_j|-1}\right\} \subseteq N_f$, and

(4) Each node is visited by one and only one vehicle, i.e., $\bigcap_{j=1}^{|V|} R_j = |N| \wedge \bigcup_{j=1}^{|V|} R_j = N$.

There are alternative representations, such as that used by Crevier, Cordeau, and Laporte (2007) and (Surekha & Sumathi, 2011) for MDVRP, but this notation is consistent with publications in agricultural machinery (D. D. Bochtis & Sørensen, 2009; Seyyedhasani & Dvorak, 2017). The next step in conversion of the field work problem into a DMDVRP is to define the fitness function through which evaluation of the optimization criteria for the parameters of interest will be carried out. The variable of primary concern, as the main, traditional objective in most VRPs, is the sum of the travel cost of vehicles:

(3.1)

$$cost_{all} = \sum_{a \in N} \sum_{b \in N} c_{ab} x_{ab}$$

where x_{ab} is a binary variable, which is 1 if a route, R_j, in the generated solution includes a connection between nodes a and b. The objective of the equation is to minimized the cost, min($cost_{all}$). The equation (3.1) considers reduction of the total work time of the vehicles. However, completion time of the field is another primary variable of concern which is defined as the travel cost of the vehicle with the highest cost as it would be the last one finishes the task:

(3.2)

$$cost_{last} = max_{j|j \in V} \left(\sum_{a \in N} \sum_{b \in N} c_{ab} x_{abj} \right)$$

As with the $cost_{all}$ variable, minimization of the $cost_{last}$ is the objective of the equation (3.2) known as min-max objective (Applegate, Cook, Dash, & Rohe, 2002; Carlsson, Ge, Subramaniam, Wu, & Ye, 2009).

As farmers are interested in minimizing the field completion time as well as the total field work by the vehicles, simple consideration of equation (3.1) or (3.3) for optimization is not suitable. Equation (3.1) only considers the travel time of the last vehicle to finish and ignores any optimization of other vehicles. Likewise, the equation (3.3) only reflects the total travel time and disregards the optimization of field completion time. Therefore, a fitness function based on weighted sum was defined to provide the improvement of both objectives:

(3.3)

$$\min\left(z\, cost_{last} + (1-z)\frac{cost_{all}}{|V|}\right), z|0 \le z \le 1$$

where z represents the proportion of the focus placed upon optimization of field completion time versus the total field work. Utilizing a weighting function enables adjusting the focus of the optimization for producers who may want a balance between the field completion time and the total field work. To ensure the weighting variable appropriately reflects the percentage of focus on each part of the equation, the total travel time, $cost_{all}$, is divided by the number of vehicles deployed. In this study, the primary focus was placed on the minimization of the field completion time. In the initial testing, the weighting coefficient of 0.8 was found to provide acceptable optimization for both objectives with a focus on field completion time.

3.3.4 Travel Cost

To solve a DMDVRP, the cost matrix which contains the traversal cost between every pair of nodes, c_{ab}, must be formed. To that end, let *C* be a $|N| \times |N|$ matrix with the elements of $c_{ab} = c_{ba}$, where c is the travel cost from node a to node b when $a \neq b$ and zero otherwise. Each track consists of a two endpoints and a midpoint. For the connection between a midpoint and an endpoint on the same track, the cost of the corresponding arc is assigned as travel cost for the vehicle to travel from the midpoint to the endpoint of the track. Other connections to the midpoints were considered invalid to force each vehicle to finish the second half of the track if the first half is started. As such the costs on those connections were set to *M*, where *M* is a large number, to significantly penalize solutions that use invalid arcs. For connections between endpoints, the cost is considered M when both endpoints are on the same track. For connections between endpoints not on the same track, the cost was assigned as the travel cost for the vehicles to travel from one track to the other. However, for travel between endpoints not in the same side of the field, the vehicles were not allowed to cross the field, i.e., the vehicles should reach the other endpoint by traveling in the headland around the field. In addition, even though the dynamic depots are considered as regular nodes for solution generation, direct connections between them were disallowed by setting their connections equal to *M*. Therefore, matrix *C* can be written as represented in Table 3-1.

Table 3-1. Representation of the cost matrix

		Track 1			Track 2			…	Final Field Node	Dynamic Depots				Stop Depot
		Endpoint	Midpoint	Endpoint	Endpoint	Midpoint	Endpoint	⋮	Endpoint	Vehicle 1	Vehicle 2	…	Vehicle N_v	
Track 1	Endpoint	0	c_{12}	M	c_{14}	M	c_{16}	…	$c_{1.\|N_f\|}$	$c_{1.\|N_f\|+1}$	$c_{1.\|N_f\|+2}$	…	$c_{1.\|N_f\|+\|N_v\|}$	$c_{1.\|N\|}$
	Midpoint	c_{21}	0	c_{23}	M	M	M	…	M	M	M	…	M	M
	Endpoint	M	c_{32}	0	c_{34}	M	c_{36}	…	$c_{3.\|N_f\|}$	$c_{3.\|N_f\|+1}$	$c_{3.\|N_f\|+2}$	…	$c_{3.\|N_f\|+\|N_v\|}$	$c_{3.\|N\|}$
Track 2	Endpoint	c_{14}	M	0	0	c_{45}	M	…	$c_{4.\|N_f\|}$	$c_{4.\|N_f\|+1}$	$c_{4.\|N_f\|+2}$	…	$c_{4.\|N_f\|+\|N_v\|}$	$c_{4.\|N\|}$
	Midpoint	M	M	c_{43}	c_{54}	0	c_{56}	…	M	M	M	…	M	M
	Endpoint	c_{61}	M	c_{63}	M	c_{65}	0	…	$c_{6.\|N_f\|}$	$c_{6.\|N_f\|+1}$	$c_{6.\|N_f\|+2}$	…	$c_{6.\|N_f\|+\|N_v\|}$	$c_{6.\|N\|}$
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Final Field Node	Endpoint	$c_{\|N_f\|.1}$	M	$c_{\|N_f\|.3}$	$c_{\|N_f\|.4}$	M	$c_{\|N_f\|.6}$	…	$c_{\|N_f\|.\|N_f\|}$	$c_{\|N_f\|.\|N_f\|+1}$	$c_{\|N_f\|.\|N_f\|+2}$	…	$c_{\|N_f\|.\|N_f\|N_v\|}$	$c_{\|N_f\|.\|N\|}$
Dynamic Depots	Vehicle 1	$c_{\|N_f\|+1.1}$	M	$c_{\|N_f\|+1.3}$	$c_{\|N_f\|+1.4}$	M	$c_{\|N_f\|+1.6}$	…	$c_{\|N_f\|+1.\|N_f\|}$	0	M	…	M	$c_{\|N_f\|+1.\|N\|}$
	Vehicle 2	$c_{\|N_f\|+2.1}$	M	$c_{\|N_f\|+2.3}$	$c_{\|N_f\|+2.4}$	M	$c_{\|N_f\|+2.6}$	…	$c_{\|N_f\|+2.\|N_f\|}$	M	0	…	M	$c_{\|N_f\|+2.\|N\|}$
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	Vehicle N_v	$c_{\|N_f\|+\|N_v\|1}$	M	$c_{\|N_f\|+\|N_v\|.3}$	$c_{\|N_f\|+\|N_v\|.4}$	M	$c_{\|N_f\|+\|N_v\|.6}$	…	$c_{\|N_f\|+\|N_v\|.\|N_f\|}$	M	M	…	0	$c_{\|N_f\|+\|N_v\|.\|N\|}$
Stop Depot		$c_{\|N\|.1}$	M	$c_{\|N\|.3}$	$c_{\|N\|.4}$	M	$c_{\|N\|.6}$	…	$c_{\|N\|.\|N_f\|}$	$c_{\|N\|.\|N_f\|+1}$	$c_{\|N\|.\|N_f\|+2}$	…	$c_{\|N\|.\|N_f\|+\|N_v\|}$	0

3.3.5 Machinery Operation Parameters of Interest

The two primary variables pursued in fitness function also underlie the parameters of interest to producers. Effective field capacity, the total field area worked divided by the time until the work is completed (American Society of Agricultural and Biological Engineers, 2011), is of paramount importance. Minimizing the field time ($cost_{last}$), which is the time from the start of field work to its completion (American Society of Agricultural and Biological Engineers, 2011), improves the effective field capacity. Another valuable parameter to farmers is field efficiency, ratio of the theoretical travel time of the vehicles to the actual time (American Society of Agricultural and Biological Engineers, 2011). This parameter is associated with the operating time of the field work. As such minimizing the total work time variable ($cost_{all}$) contributes to field efficiency.

3.4 DMDVRP SOLUTION METHODS

There are many heuristics and meta-heuristics procedures developed to provide solutions for various varieties of the VRP. However, they are not able to provide an efficient solution for the DMDVRP, so a new method was devised. The first step was to generate an initial solution, and to do so, the dynamic individual depots of the problem were assumed to be regular spatial nodes. In this way, the problem converts into the standard VRP. Then a modified Clarke-Wright Savings Algorithm as a heuristic procedure is used to generate an initial solution. Finally, a more optimal solution was produced through application of the Tabu Search Algorithm, which is a meta-heuristic procedure.

3.4.1 Initial Solution from Modified Clarke-Wright

The Clarke-Wright Savings Algorithm (Clarke & Wright, 1964), as a cost saving procedure, strives to reduce the cost for a fleet of vehicles in which capacity is considered an important constraint. In case of the problem investigated in this paper, capacity is assumed infinite (that is, the agricultural operations in which capacity is not considered a limitation). Therefore, the Clarke-Wright algorithm tends to produce an overall route consisting of all the nodes. This becomes a reasonable solution for a single vehicle covering the area, whereas it is inappropriate for task allocation for multiple vehicles.

Figure 3 demonstrates the single long route servicing all the nodes generated by the basic Clarke-Wright Algorithm, while considering the dynamic individual depots as regular nodes.

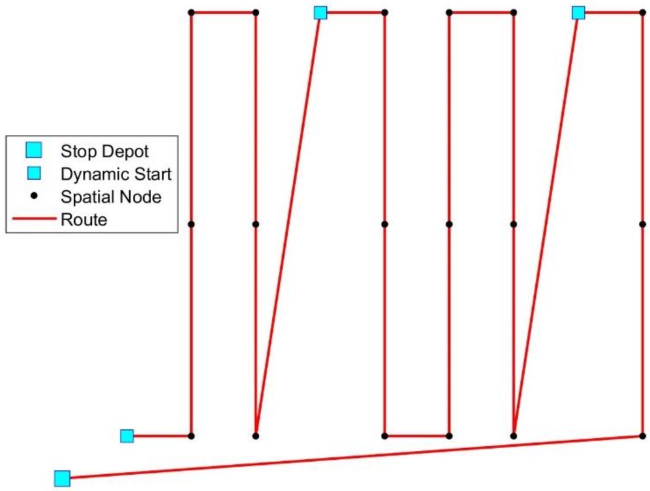


Figure 3-4. A single long route generated by basic Clarke-Wright Algorithm

This single route was then distributed among available vehicles by dividing the single route into multiple routes using the dynamic start depots. For route allocation to specific vehicles, a number of approaches are evaluated by the procedure: 1) each vehicle adopts the subsequent nodes from its current location until it reaches the next dynamic start node; 2) reversed version of the prior method through linking the end node to the first dynamic start node; 3) after linking the end node to the first dynamic start node, the first vehicle adopts its surrounding nodes until it reaches a dynamic start node from either side, and other vehicles split the remaining route. After completing its route, each vehicle travels back to the main depot. The allocation takes place based on the method that best meets the established optimization criteria and most reduces the cost of fitness function (Figure 2(a)). The result is an acceptable solution for this class of agricultural field work problem which requires insignificant computation time to be generated. The solution as displayed in Figure 2(b) is based on the exact location of the vehicles where re-routing was initiated.

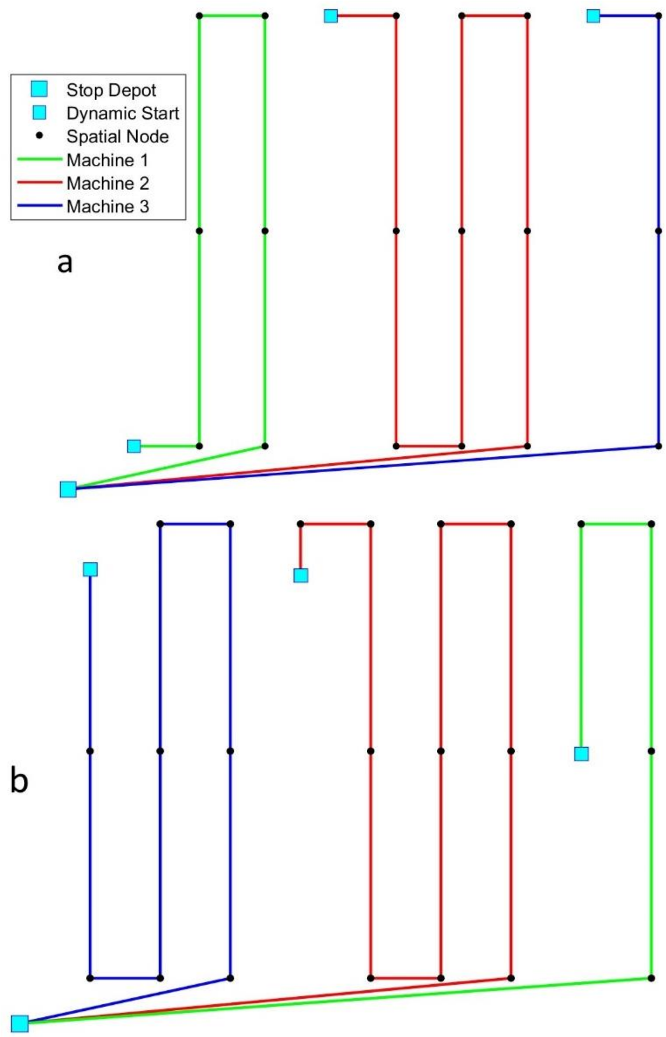


Figure 3-5. Modified Clarke-Wright algorithm solution

3.4.2 Further Optimization

Tabu Search was then used to perform optimization of the initial routes. As a meta-heuristic, Tabu Search developed by Glover (1989) relies on iterations to investigate potential solutions and incrementally produces increasingly more optimal solutions. The technique has been proved to generate highly effective solutions for MDVRP (Cordeau, Gendreau, & Laporte, 1997; Crevier et al., 2007). It is a powerful optimization technique and in other agriculture applications has been used to improve enterprise-level planning of the order in which fields should be worked (Edwards, Bochtis, & Søresen, 2013). In this work, Tabu Search was implemented as described in Seyyedhasani and Dvorak (2017), which provides more details on computational complexity and use.

3.5 TEST SCENARIOS

An experiment was designed to investigate solutions provided by the computer model developed for re-routing the vehicles involved in an operation, in an ongoing fashion. The field selected for the experiment was located in Logan County, Kentucky, United States of America [36.793°, -86.77°] (Figure 9). The field was of a non-convex shape with an area of approximately 71.5 ha. The producer often uses three vehicles in field operations in this field and the field paths within the field were those used by the producer during an anhydrous ammonia application. The field work parameters for this operation were 73% for the field efficiency and 10.0 ha h^{-1} for the effective field capacity.

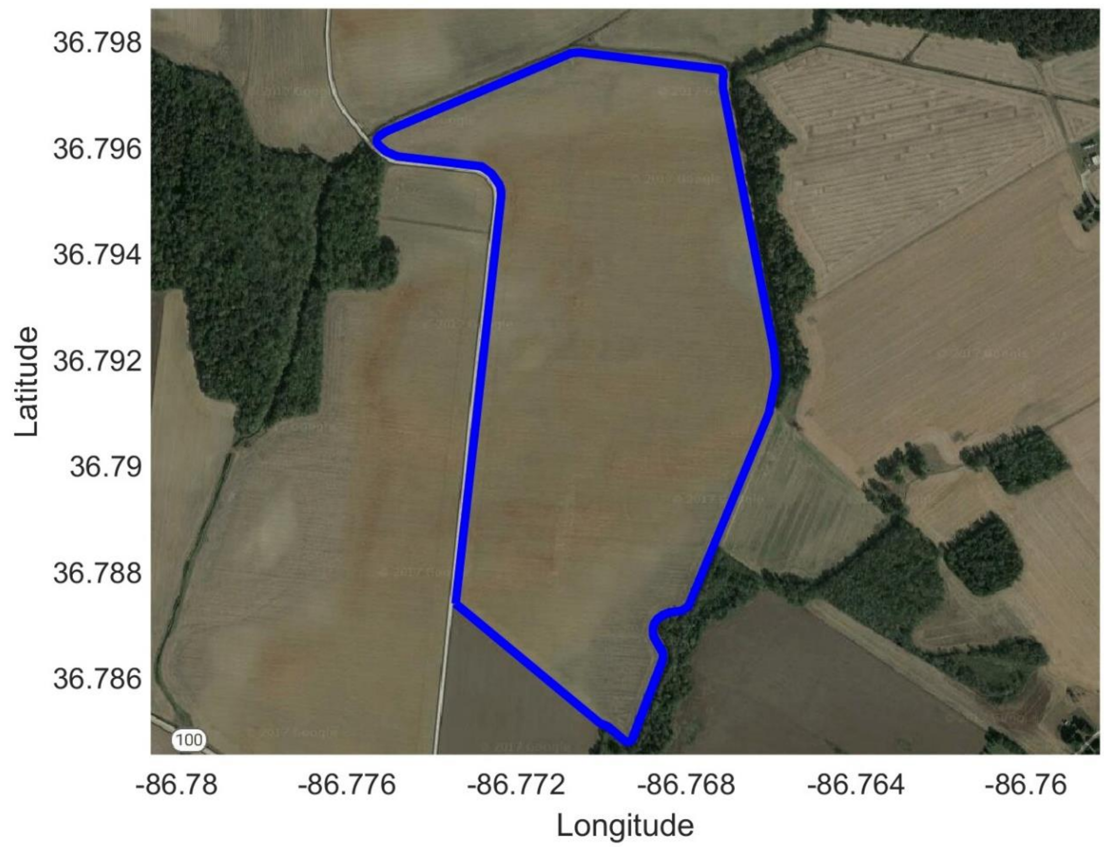


Figure 3-6. Field selected for the experiment

3.5.1 Base Scenario

Path allocation and route planning for each vehicle involved in the operation was performed using the optimization procedure developed by Seyyedhasani and Dvorak (2017). Three VRP nodes were assigned to each field path (Figure 3-7). Path allocation produced routes that start and end at the field entrance for each of the three vehicles (Figure 3-8). If this base scenario were followed to completion, the procedure estimates that it would take 113 minutes to complete the field. Field efficiency was calculated for each vehicle route from the start of field work until that route was completed. The average field efficiency for the complete set of vehicle routes was 87%. Field capacity per vehicle was also determined, but this calculation was performed in aggregate by dividing the total area worked by the time required to work that area and the number of vehicles used. The field capacity per vehicle for the complete set of routes in the base scenario was 13.5 ha h^{-1}.

Three different scenarios were considered as triggers for dynamic re-routing: 1) re-routing following changes in the number of vehicles, 2) re-routing arising from unexpected behaviors (working speed) of the vehicles, and 3) re-routing due to changes in area coverage. Most scenarios were tested with the trigger event and re-routing occurring after 28, 56, and 84 minutes of work. These times correspond to when the initial solution predicted that 75%, 50% and 25% of the field work remained.

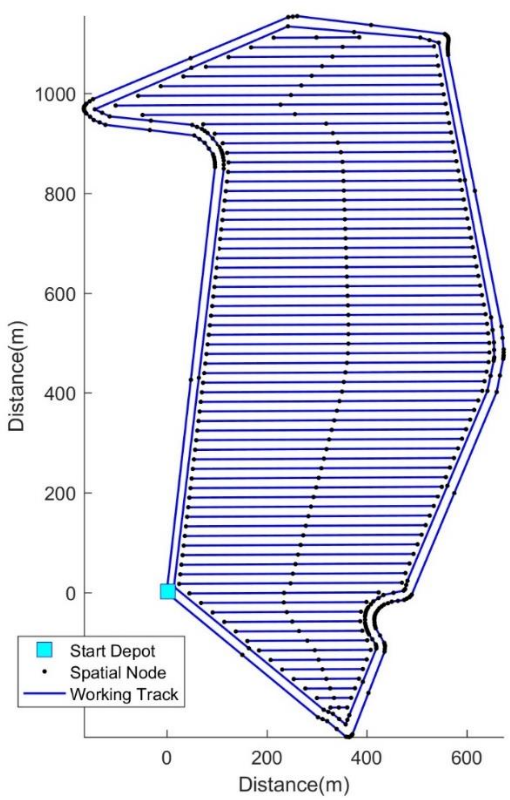


Figure 3-7. Field paths to be worked (blue lines) with VRP nodes (black dots) assigned.

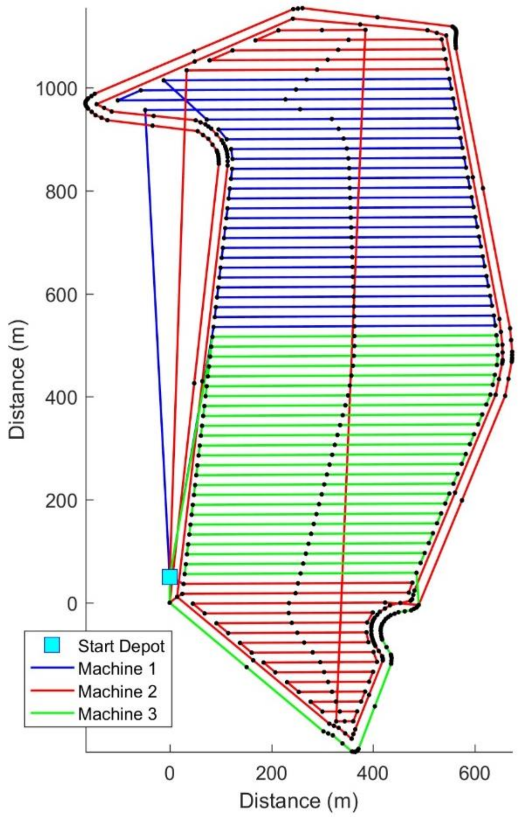


Figure 3-8. Vehicle routes for three machines following the optimization procedure in Seyyedhasani and Dvorak (2017). All routes start and stop at the field entrance (Start Depot).

3.5.2 Scenario 1: Change in Number of Vehicles

In the initial solution, three vehicles were involved in the field operation from the beginning to the end of the operation. This scenario considers two actions: the addition or the removal of a single vehicle from the fleet of vehicles working in the field. In this scenario, the change happens suddenly at times of 28, 56, and 84 minutes after starting the field work. The vehicles are assumed to have perfectly followed the initial solution for the base scenario up to this point in time (Figure 3-9). For vehicle removal, vehicle 2 is removed from service instantaneously at the trigger time. The path on which vehicle 2 was working is incomplete and the entire path is assigned to another vehicle. This results in a slight loss of completed work in the vehicle removal scenario.

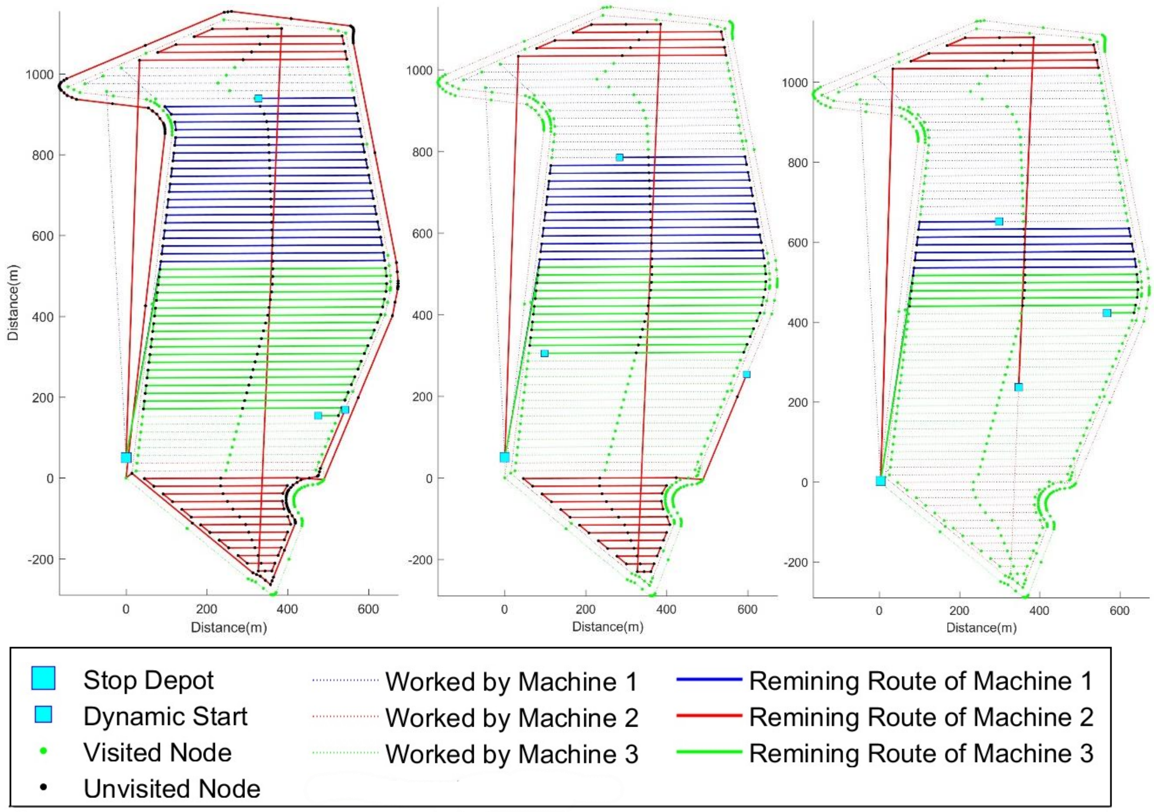


Figure 3-9. Field completion based on the base scenario with field working times of (a) 28, (b) 56, (c) 84 minutes

3.5.3 Scenario 2: Unexpected Field Work Rates

In this scenario, Vehicle 2 has unexpectedly managed to complete 30% more field work than anticipated in the base scenario. It is assumed that this increase occurs and/or is noticed at the same operating times as scenario 1: 28, 56, and 84 minutes. However, since Vehicle 2 has completed 30% more work, more of the field has been completed at these times than at the same times in scenario 1 (Figure 3-10). The increase in the work rate for Vehicle 2 is temporary. While it has completed 30% more work than predicted at 28, 56, and 84 minutes, for the remainder of the field, it will operate at its standard rate. Because Vehicle 2 completed more work than expected in all of these scenarios, it is expected to complete its initial route quicker even as it finishes its route at the expected rate. If no changes to routes are made, Vehicle 2 is assumed to wait at the final depot until all other vehicles also finish.

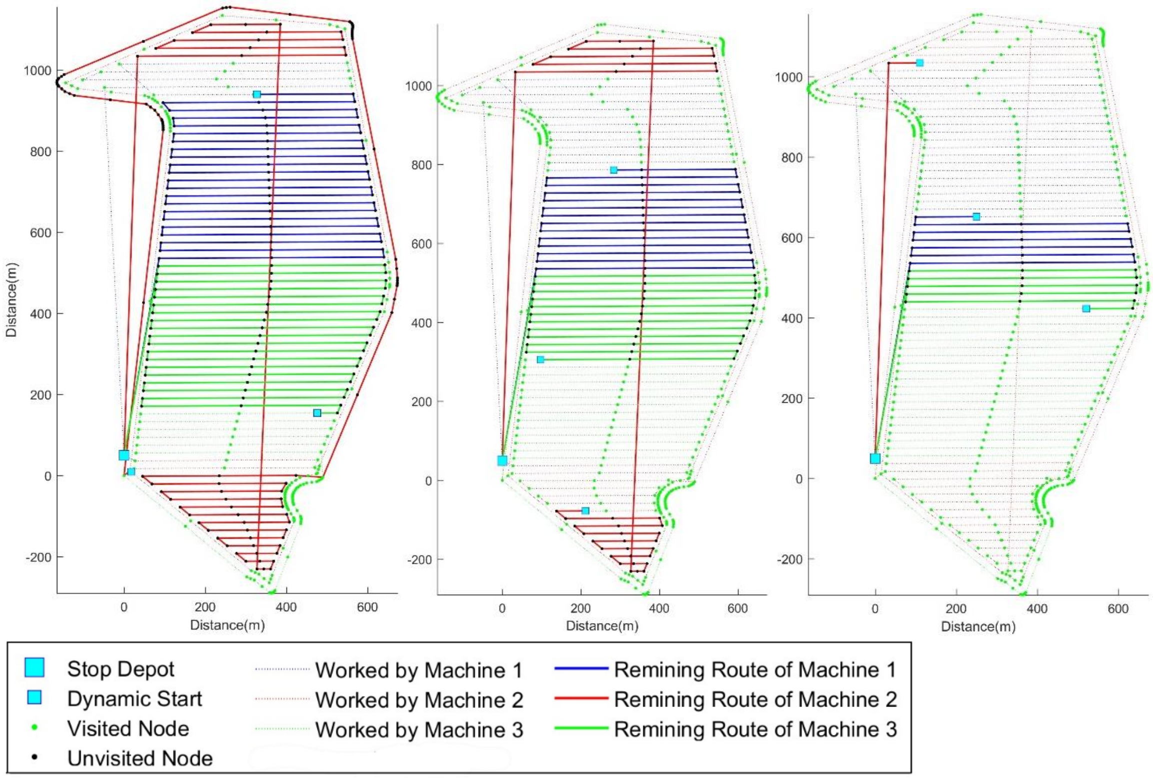


Figure 3-10. Remaining paths when a) 75%, b) 50%, and c) 25% of the paths assigned to each vehicle should be left, according to the initial path allocation

3.5.4 Scenario 3: Changes in Area to Be Worked

In this scenario, re-routing takes place when sections are added or removed from the field area to be worked. For section removal, the vehicles begin with the base scenario. They work the field until one of the vehicles encounters the area to be removed. At this point, the paths in this section of the field are removed from the field area to be worked (Figure 3-11). This occurs after 42 minutes of work in the field. The initial vehicle routes are no longer valid and the re-routing procedure is used to generate a new set of routes that does not include the removed section of the field.

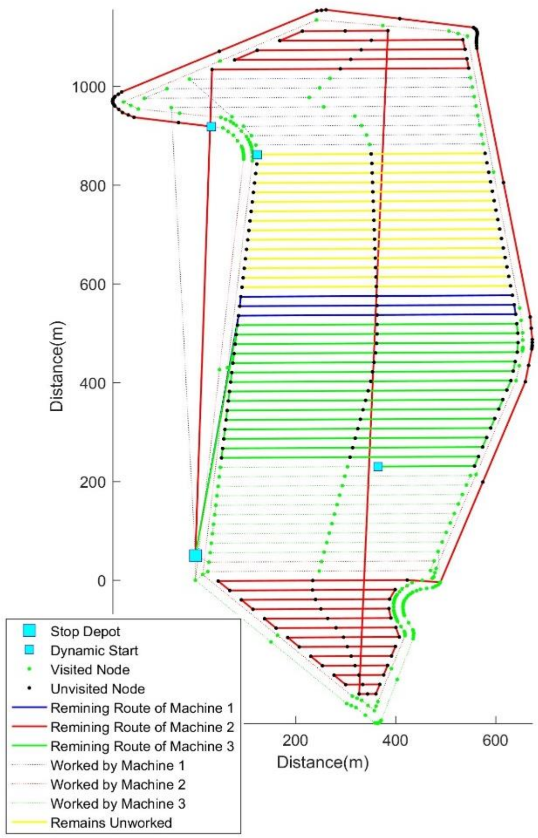


Figure 3-11. The area (and the corresponding work paths) to be removed from the field work plan is shown in yellow. Vehicle progress in working the field is also shown for the moment at which a vehicle (Vehicle 1) first encounters the section to be removed. The re-routing process begins at this stage.

When adding a section to the field, the base scenario is different from the other scenarios. The initial solution is the base field with a section already removed (Figure 3-12). The predicted time to complete this field work is 86 minutes. The expected field capacity is 14.1 ha hr^{-1} and the field efficiency is 90.7%. In testing, the missing section of the original field is added to the work plan when the field has been worked for 22, 43, and 65 minutes (Figure 3-13). These times correspond to when 75, 50, and 25% of the field is remaining.

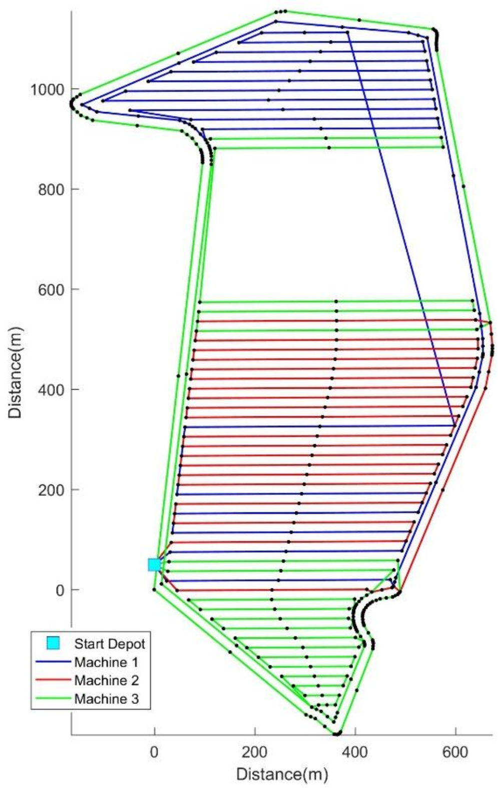


Figure 3-12. Original solution for the field with one section removed from the work plan.

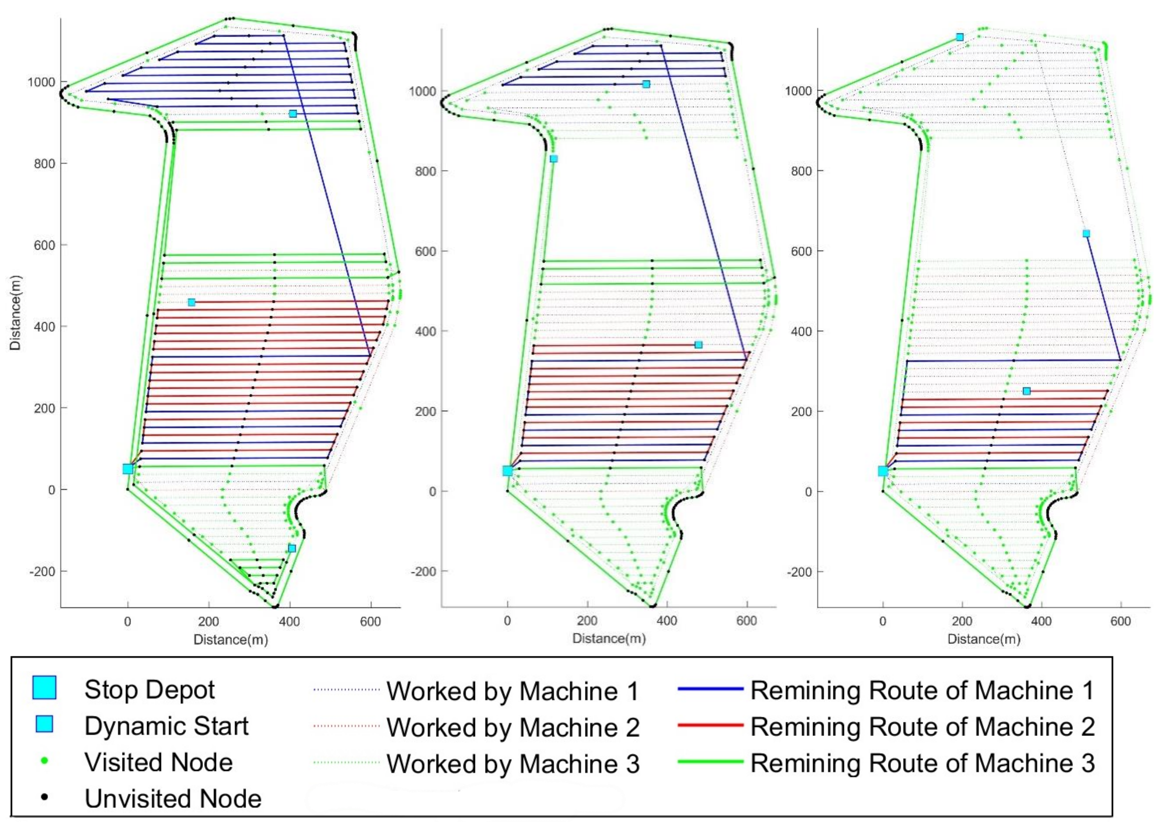


Figure 3-13. Field completion based on the base scenario with field working times of (a) 22, (b) 46, (c) 65 minutes

3.5.5 Evaluating the Effectiveness of Re-routing

In all of the scenarios, a pre-calculated base scenario is followed until an event occurs which triggers the need for re-routing. For evaluation, the field capacity per vehicle and field efficiency are calculated for both the initial routes and the newly recalculated routes following the trigger event. For example, for a scenario with a trigger event at 56 minutes (when 50% of the field work is completed), values for field capacity per vehicle and field efficiency are based on vehicle travel from the trigger time, at 56 minutes, to field completion. Comparing only the values after the trigger event highlights differences directly caused by the re-routing and ensures that these differences are not diluted by averaging over the entire field working time.

Vehicle operation is expressed based on both average field efficiency and field capacity per vehicle. In general, these terms are associated; however, differences arise when one vehicle finishes its route before the other. The average field efficiency is the average of each vehicle's field efficiency as it follows its route. The field capacity per vehicle is the total area worked divided by the time required and number of vehicles available. A vehicle that finishes its route will no longer see changes in its field efficiency. However, if the field is still not complete, field capacity will be impacted as that vehicle is available for use but is not contributing to field work progress.

3.6 Results and Discussion

3.6.1 Scenario 1: Change in Number of Vehicles

The new paths generated by the path assignment are unpredictable as the procedure optimizes the allocation between available vehicles. Figure 3-14 and Figure 3-15 show the optimized paths for the case in which a vehicle is removed (Figure 3-14) or added (Figure 3-15) after 56 minutes of field work (field is 50% complete).

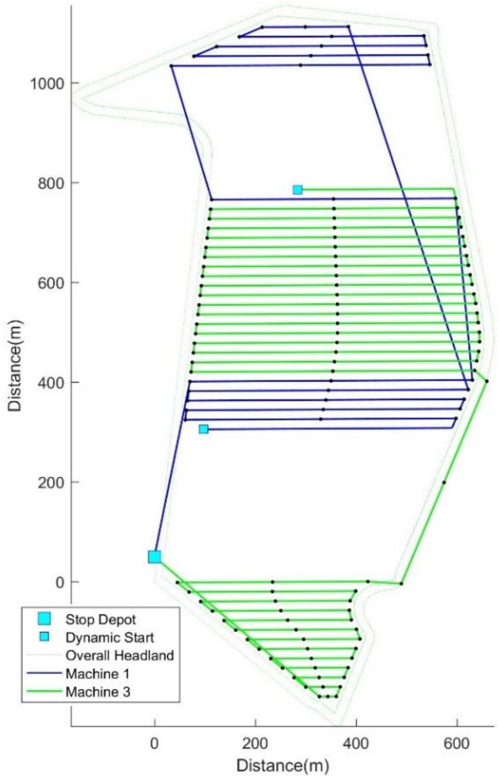


Figure 3-14. New routes created by the scenario in which Vehicle 2 is removed after working in the field for 56 minutes.

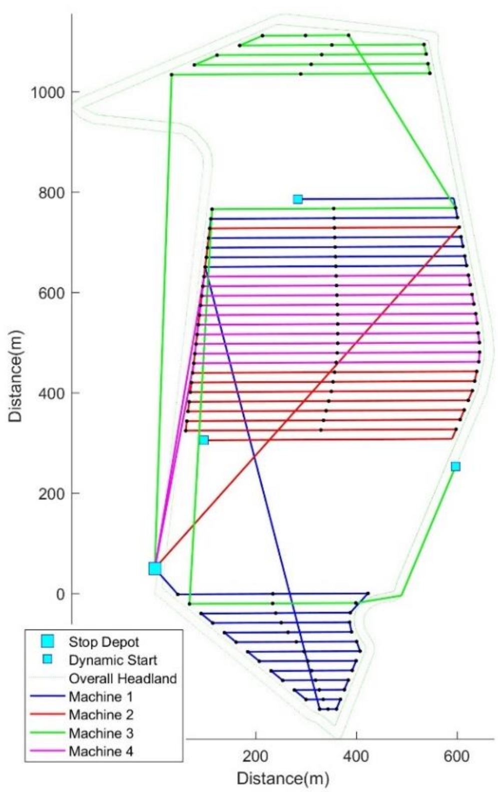


Figure 3-15. New routes created by the scenario in which a fourth vehicle is added after 56 minutes of field work.

Changing the number of vehicles available to work the field had significant effects on the important field work management parameters of average field efficiency, field capacity per vehicle and time required to complete the field (Table 3-2). Routes in all cases were most efficient at the beginning as longer non-working travel paths were concentrated at the end of the routes. This produced a general decrease in average field efficiency and field capacity per vehicle as more of the field is completed. As expected, removing a vehicle increased the time required to finish the field and adding a vehicle decreased that time with the magnitude of the change dependent on when the vehicle was added or removed.

Removing a vehicle also increased average field efficiency, but adding a vehicle decreased it. This is expected, as utilizing more vehicles requires more non-working travel to reach different field sections. The effect on field capacity per vehicle was less consistent and not related to the time of the trigging event or whether a vehicle was added or removed. In half of the cases, field capacity was largely unchanged and remained within ±5% of the values in the initial solution. In the remaining cases, field capacity per vehicle decreased by 12.3% to 19.8%, which represents cases in which the updating procedure had difficulty identifying a solution that was as optimal as the original.

Table 3-2. Effective field capacity and field efficiency following the triggering event for the scenario with the removal or addition of a vehicle. Percent change from the initial solution to the updated solution is shown in parenthesis following values in the updated solution column.

Scenario	Parameters	Base Scenario [a]	Initial Solution			Updated Solution		
	Elapsed time at which scenario is triggered (min)	**Never**	**28**	**56**	**84**	**28**	**56**	**84**
Removal of One Vehicle	Effective Field Capacity per Vehicle (ha h^{-1})	13.5	13.5	12.6	11.4	13.8 (2.5%)	10.4 (-17.2%)	11.8 (2.8%)
	Field Efficiency (%)	86.8	82.3	82	76.5	92.3 (12.2%)	85.6 (4.4%)	81.5 (6.5%)
	Remaining Time to Field Completion (min)	113	85	57	29	125 (47%)	104 (82.5%)	43 (48.3%)
Addition of One Vehicle	Effective Field Capacity per Vehicle (ha h^{-1})	13.5	13.4	12.5	10.8	12.7 (-4.9%)	10.9 (-12.3%)	8.68 (-19.8%)
	Field Efficiency (%)	86.8	86.5	81.3	72.3	84.7 (-2.1%)	74.5 (-8.3%)	75 (3.7%)
	Remaining Time to Field Completion (min)	113	85	57	29	67 (-21.2%)	49 (-14%)	27 (-6.9%)

[a] The base scenario column represents following the initial solution all the way to completion and never adding or removing a vehicle. It is provided for comparison.

An important area of further study would be to identify the factors that make it difficult for the optimization procedure to produce better routes and ways to mitigate those factors. Although the procedure had difficulty in maintaining previous levels of field capacity per vehicle in some cases, it was always able to reroute the vehicles to improve field completion time (for addition of a vehicle) or field efficiency (for removal of a vehicle). This illustrates that the updating procedure can provide effective new routes in the event of a change in the number of vehicles available to work a field.

3.6.2 Scenario 2: Unexpected Field Work Rates

When field work does not proceed at expected rates, significant improvements to field work parameters can be made using a real-time updating procedure (Table 3-3). In this particular test, vehicle 2 has been able to complete 30% more work than expected at the event triggering time. If the vehicles remain on their initial routes, vehicle 2 will complete the field earlier and sit at the gate waiting for the other vehicles to finish. Following the initial routes to completion will result in total field completion time remaining at 113 minutes as the other vehicles still require the full 113 minutes to complete their routes. Redistributing the field paths allows vehicle 2 to take over the paths of the other vehicles and enables all of them to complete the field in less time. The gains in completion time from rerouting are more dependent on the level of the disruption to the original working plan than on the rerouting procedure. The largest reductions in field completion time occurring when vehicle 2 operated for the longest period with an increased work rate (corresponding to later trigger times), but without a rerouting procedure, it would be impossible to realize any of these gains.

Table 3-3. Effective field capacity and field efficiency following the triggering event for the scenario in which a vehicle unexpected works at a higher rate. Percent change from the initial solution to the updated solution is shown in parenthesis following values in the updated solution column.

Scenario	**Parameters**	**Base Scenario** [a]	**Initial Solution**			**Updated Solution**		
	Elapsed time at which scenario is triggered (min)	**Never**	**28**	**56**	**84**	**28**	**56**	**84**
Unexpected field work rate	Effective Field Capacity per Vehicle (ha h^{-1})	13.5	12.9	11.3	8.4	13.2 (2.2%)	11.9 (5.2%)	10.2 (21.2%)
	Field Efficiency (%)	86.8	86	80.4	74.7	85 (-1.3%)	78 (-2.9%)	75 (0.4%)
	Remaining Time to Field Completion (min)	113	85	57	29	83 (-2.3%)	54 (-5.3%)	24 (-17.2%)

[a] The base scenario column represents following the initial solution all the way to completion with vehicle 2 at its expected work rate. It is provided for comparison.

The effective field capacity also illustrates the importance of route updates when field work does not proceed as expected. The idle time for vehicle 2 in the initial solution causes a sharp drop in field capacity per vehicle. In the base scenario, field capacity per vehicle is 13.5 ha h^{-1}, but it decreases to 8.4 ha h^{-1} with later trigger times for the scenario. Rerouting prevents vehicle 2 from sitting idle and the effective field capacity increases to 10.2 ha h^{-1}, which is a 21.2% increase.

Finally, the results with average field efficiency illustrate that the new routes generated by the procedure are still efficient. The average field efficiency of the routes remains within 3% of the original routes. The rerouting procedure performed very well in this scenario as it was able to provide reductions to field completion times, increases in field capacity and maintain the field efficiency of the individual machine routes.

3.6.3 Scenario 3: Changes in Area to be Worked

Unlike the other scenarios considered, changes in area to be worked force rerouting and reallocation of vehicle paths as the original routes either include areas that should not be worked or are missing areas that should. This prevents direct comparisons between the newly updated routes and the initial routes from different rerouting triggering points. Instead, comparisons are made between the new routes and the initial set of routes had the area remained constant. This provides two base scenarios. One base scenario was generated using the smaller field area with a section removed. The other is the original base scenario used in the other scenarios. This larger base scenario covers the entire field area.

When a section of field is added, the vehicle initially starts with the small base scenario, but then must switch to completing the area covered by the large base scenario at the scenario trigger time. The route updating procedure worked well in handling this change as there were only minor adjustments in the field work parameters (Table 3-4). The field completion time for the base scenario that includes the entire field was 113 minutes. In the worst case, the updated routes required 114 minutes. At two of the area change trigger points, the updated solution actually produced results that decreased the time to complete the field. Additionally, field capacity per vehicle and field efficiency for the routes only experience slight if any decreases from the large base scenario that covers the entire field. Field efficiency only drops from 86.8% to 84.6%, and field capacity per vehicle only drops from 13.5 ha h^{-1} to 12.6 ha h^{-1} for the updated solution beginning at 65 minutes after starting the field. Route updating and optimization works very well when the field size is increased with resulting field completion times very close to the times provided when the size of the field was known from the beginning of the field work.

Table 3-4. Effective field capacity and field efficiency following the triggering event for the scenario with the addition of a section of field.

Scenario	**Parameters**	**Small Base Scenario [a]**	**Large Base Scenario [b]**	**Updated Solution**		
	Elapsed time at which scenario is triggered (min)	**Never**	**Never**	**22**	**43**	**65**
Addition of Field Section	Effective Field Capacity per Vehicle (ha h^{-1})	14.1	13.5	13.1	13.7	12.6
	Field Efficiency	90.7	86.8	86.1	87.6	84.6
	Remaining Time to Field Completion (min)	--	--	92	65	47
	Total Field Completion Time (min)	86	113	114	108	112

[a] The small base scenario column shows the parameter values for a solution that works the field with the section removed from the beginning to completion.
[b] The large base scenario column shows the parameter values for the original base scenario solution produced for working the entire field from the beginning to completion.

Real-time path reallocation, optimization and updating did not work as well for the removal of a section from the field as it did for the addition of section to the field. When removal of the particular section of the coverage area happens, the base scenario turns into the small base scenario. The new paths are reasonable, as the field work parameters are slightly less than those for the base scenario (Table 3-5). However, compared to the pre-calculated solution for the small base scenario, the magnitude of the field completion time, field capacity, and field efficiency all declined by approximately 8%. Unlike the section addition scenario in which field completion times were almost unchanged compared to final area, in this section removal scenario, total field completion time increased by 8 minutes. This is not unexpected as resetting the paths instantaneously after the first machine (vehicle 1) arrived to the “Remains Unworked” region increased non-working travel unexpectedly — both to get to the "Remains Unworked" region, according to the initial solution, and to get to the newly allocated spot after reallocation (Figure 3-16).

Table 3-5. Effective field capacity and field efficiency for the entire field work for the scenario with the removal of a section of field.

Scenario	**Parameters**	**Small Base Scenario [a]**	**Large Base Scenario [b]**	**Updated Solution**
	Elapsed time at which scenario is triggered (min)	**Never**	**Never**	**42**
Removal of Field Section	Effective Field Capacity per Vehicle (ha h^{-1})	14.1	13.5	13
	Field Efficiency	90.7	86.8	84.9
	Remaining Time to Field Completion (min)	--	--	54
	Total Field Completion Time (min)	86	113	96

[a] The small base scenario column shows the parameter values for a solution that works the field with the section removed from the beginning to completion.
[b] The large base scenario column shows the parameter values for the original base scenario solution produced for working the entire field from the beginning to completion.

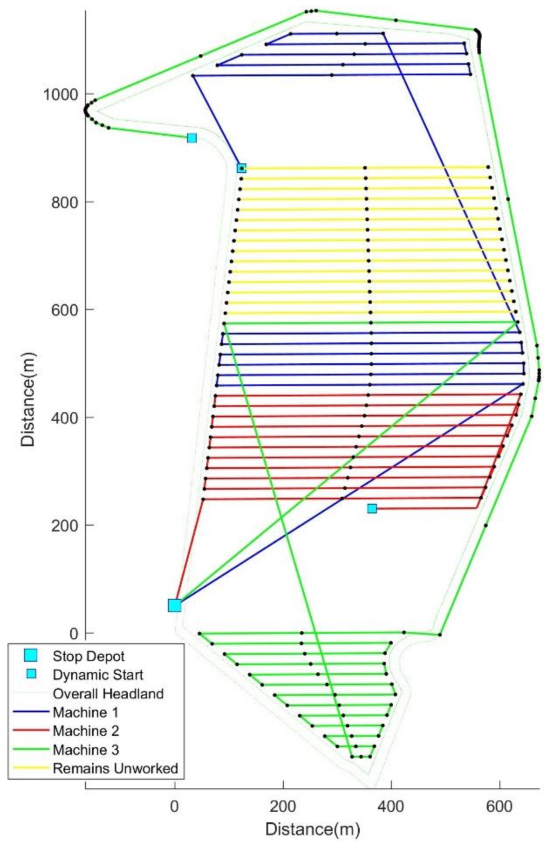


Figure 3-16. Removing a plot from the field work while operation

3.6.4 Overall Discussion

In many of the tested cases, the effectiveness of the rerouting procedure was largely dependent on the routing flexibility remaining for the field work. For example, when a vehicle is added to the field, the earlier this addition happens, the larger the percent decrease in field completion time. For the changes in field area, an increase in area raises the number of available paths and flexibility. In this case, the field work parameters were largely the same as if the area were constant from the beginning. However, a decrease in area reduces the flexibility, and the field work parameters moved in a worse direction. Although the updating procedure permits sudden changes to the field work conditions, it is still best to determine these settings as early as possible to maximize effectiveness of the field work.

3.7 CONCLUSIONS

The ability to provide dynamic, real-time updating to vehicle path allocations is an important characteristic of any useful method to optimize the routes of multiple vehicles working together in agricultural fields. The mathematical representation of the field and solution algorithms provided in the methods section enables this dynamic, real-time optimization. In all the scenarios tested, this procedure was able to produce new optimized routes, but the impact of these routes varied for each scenario. When a vehicle was added to the fleet working the field, the updating procedure was able to use that vehicle to reduce completion times, and the magnitude of the reduction was greater when more of the field was unworked. For removal of a vehicle, the field completion time increased, but the procedure was able to increase the field efficiency of the remaining vehicles. When a vehicle completes more work than expected, the updating procedure enables the producer to capture this benefit to complete the field in less time. The updating procedure is also effective in this case, as field efficiency remains within 3% of the original field efficiency. The procedure was excellent at handling increases in the field area to be worked with total field completion times largely unchanged compared with optimizations performed with a consistent field area from the beginning. However, the procedure was less capable of addressing the challenges presented by a sudden reduction of field area, with the field capacity, field efficiency and completion time moving in a worse direction by approximately 8% each. In general, the procedure was able to provide better outcomes if the change in field conditions occurred at a point in time when less of the field was complete and there was more flexibility in the final routing. This project illustrates that it is possible to update field routes for a fleet of vehicles during field operations. The impact of the new routes is dependent on the specifics of the event that necessitated the rerouting, but such a system provides the opportunity to improve field work outcomes based on changing and variable field and work conditions.

CHAPTER 4: OBJECTIVE 3: REDUCING FIELD WORK TIME USING FLEET ROUTING OPTIMIZATION

4.1 SUMMARY

Agricultural producers seek to complete their field work operations as quickly as possible. This is achievable through the simultaneous use of multiple vehicles for an operation. However, path allocation and scheduling then must be considered. Transforming the field work problem into a Vehicle Routing Problem (VRP) and using optimization procedures designed for this problem provides a method of allocating paths. In this work, the accuracy of a VRP representation of field work is confirmed and the ability of this optimization system to reduce field work times is verified. Experiments were conducted using three tractors during a rotary mowing operation. First, the traditional routes used by human drivers were recorded. Then, a VRP representation of this operation was created, and new routes generated by a Tabu Search optimization procedure. Finally, the field operation was repeated using the optimized routes. Using these routes, the time to complete the field work was reduced by 17.3% and the total operating time for all tractors was reduced by 11.5%. The predictions by the VRP representation for completion time and total time were both within 2% of the actual times recorded when the tractors followed the computer-generated routes in the field. These reductions illustrated the ability of the route optimization procedure to improve effective field efficiency.

4.2 INTRODUCTION

Agricultural producers seek to complete their field work operations as quickly as possible. This drive to increase field capacity, the rate in terms of area per time that work is done (American Society of Agricultural and Biological Engineers, 2011), has led to larger agricultural machinery and many producers to use more than one machine in a field at a time. It has also led researchers to seek methods to improve the efficiency of these field operations. Many researchers have tested methods to improve the way in which paths are generated in fields. Other projects have focused on the order in which these paths are worked and, in the case of multiple vehicles, which vehicles are assigned to each path. One issue with these improved path generation and routing systems is that the solutions they generate often appear random and arbitrary. These solutions do not follow any easily recognizable rule. However, modern advances in sensing, information and communication technologies have provided automatic steering and navigation systems that enable following these more complex paths through the field. As development continues in autonomous vehicles for both traditional field work and crop scouting, these path generation and routing techniques will become not only more feasible, but also more necessary as there will not be a human operator to generate paths and routes in the traditional manner.

Much agricultural machinery optimization research has been focused on improved algorithms for path generation (Flann, Hansen, & Gray, 2007; I. A. Hameed et al., 2011; Jin & Tang, 2010; Palmer et al., 2003). Using discrete geometric primitives and operating in real time, I. A. Hameed et al. (2010) generated maps to represent the field on which field operations take place. In addition, various methods have been developed for automatic geometric representation of field sections such as headland generation (Sachs, Roszhart, Schleicher, Beck, & Bezdek, 2012), and headland turns generation (Birnie, 2006; Senneff, Leiran, & Roszhart, 2012). When path generation, planning and routing are combined, it provides a coverage path planning algorithm. A complete coverage path planning algorithm for one vehicle using a genetic algorithm for the solution has been developed by Ibrahim A Hameed, Bochtis, and Sørensen (2013). In order to efficiently operate on the generated paths, along with operational planning also known as in-field machinery activities (I. Hameed, Bochtis, Sørensen, & Vougioukas, 2012), it is required to allocate and schedule the paths among the available vehicles. Researchers have shown that scheduling the paths efficiently can reduce the total non-productive travel up to 50% (D. D. Bochtis & Vougioukas, 2008). D. D. Bochtis and Sørensen (2010) investigated the scheduling and planning for the service units in harvest operations. They represented this operation as a Vehicle Routing Problem with Time Windows and used optimization techniques designed for this traditional computer science problem. Non-productive travelled distance can be decreased further by taking into consideration the impact of different types of headland turns (D. Bochtis, 2008; Jensen, Bochtis, & Sørensen, 2015). Ali, Verlinden, and Van Oudheusden (2009) reduced the non-productive travel time of combine harvesters by generating itineraries for the vehicles including the start location, the end location, and locations for unloading the harvester. In fertilizing operations, total travel distance was reduced up to 11.8% (Jensen et al., 2015) by following optimized plans instead of the conventional plans followed by farmers during the operations. Researchers have even explored routing optimization for vehicles to specifically reduce compaction potential (Dionysis D. Bochtis et al., 2012). They could reduce the risk factor up to 61% using optimal paths.

The variants of the Vehicle Routing Problem (VRP) provide methods to represent mathematically the routing of a fleet used to visit and service customers, contingent upon specific constraints. There are a set of constraints incorporated in the VRP which necessitate that all the customers be visited and that each individual customer be visited by only one vehicle. In addition, various variants of the VRP have their respective constraints such as the vehicles start and end positions in designated locations, or customers be visited in a specific order or in a specific time window. When applying VRP for solving a problem a network graph is developed. Each customer is transformed into a node on the graph, and the travel cost between each pair of nodes is assigned to the connection between the nodes. In agricultural applications, casting the field routing problem as a mathematical optimization problem is a powerful tool to improve logistics (D. D. Bochtis & Sørensen, 2009; Conesa-Muñoz et al., 2016).

Seyyedhasani and Dvorak (2017) proposed a VRP representation and optimization techniques that focused on enabling producers using multiple vehicles to complete a field operation as quickly as possible. The field representation began with a set of travel paths along which the agricultural vehicle drives. VRP nodes were assigned to the endpoints and midpoint of each path. In the next step, the travel time between each pair of location coordinates was assigned as the connection cost for the pair of the corresponding nodes. Connections that were considered unacceptable (e.g. from one endpoint to an endpoint at the other side of the field or from midpoint to midpoint) were penalized by assigning a very high cost. The outputs of the first two steps are a cost matrix (for optimization) and a transformation matrix (to map physical locations to nodes). An initial solution was generated using a modified version of the Clarke-Wright Savings algorithm (Clarke & Wright, 1964) and improved using Tabu Search. The Tabu Search procedure developed by Glover (1989) searches more broadly for solutions and prevents the optimization function from getting trapped at a local minimum. Each iteration of the algorithm (as the algorithm is an iteration-based procedure) utilizes all possible combinations of three operations: swap, insertion, and inversion. Tabu Search is a powerful optimization technique and has been used in other agriculture applications to improve enterprise-level planning such as calculating the sequence in which fields should be worked (Edwards et al., 2013).

According to the model developed by Seyyedhasani and Dvorak (2017), the simulation results provided feasible solutions through both the modified version of the Clarke-Wright algorithm and the Tabu Search algorithm. The modified Clarke-Wright solutions were similar to the Work Zone approach currently utilized by many producers. The Tabu Search provided less predictable routing that was unlike any route pattern currently used by producers. These simulation results proved that the proposed VRP conversion and its optimization method were feasible.

The goal of this project was to confirm the expected reduction in the time required for multiple vehicles to finish a field. To that end, field completion times to conduct an agricultural operation via conventional human-operator routing was compared to an improved routing provided by the optimization procedure in the same field. Within this larger comparison, it was also necessary to test whether the computer model was accurate and the times predicted by the optimized solution could be realized by tractors driving these routes in the field.

4.3 MATERIALS AND METHODS

Most of the field experiments in this study were performed on the University of Kentucky's C. Oran Little Research Center in Versailles, Kentucky in a recently harvested corn field in late September and early October of 2016. This Research Center is a 600-hectare farm. While the farm provides some crop test plots for researchers, much of it is managed using standard commercial crop production practices to provide the feed inputs for the animal research that also occurs there. Following corn harvest, the managers of the farm were planning to cut down the standing corn stalks using tractor-pulled rotary mowers. They intended to use multiple tractors during this field operation so it provided an opportunity to analyse standard tractor driver coordination patterns. Only minor changes to normal operating procedures were necessary to accommodate data collection. The operation took place on two contiguous fields covering 15.6 ha: a 12.1 ha field (a) and a 3.5 ha field (b) (Figure 4-1). After recording the original routes used by the tractor drivers, a set of computer-optimized routes was generated. These optimized routes were then tested by repeating the field operation using the new routes to confirm the expected efficiency improvements.

Figure 4-1. The two contiguous fields in University of Kentucky C. Oran Little Research Center

A second operation was recorded on a farm in Logan County, Kentucky. The field had a non-convex boundary with the area of approximately 71.5 ha (Figure 4-2), in which three vehicles worked together applying anhydrous ammonia to cover the whole field. In this field, the operation was not repeated. Only the original routes were recorded. The data from this field was only used to verify that the travel time estimates provided by the cost matrix were accurate. As this operation was an application of anhydrous ammonia, the recorded routes included travel to reposition anhydrous ammonia tanks in the field. This project only focuses on travel and working times, not refill and equipment servicing times, so this tank repositioning time was removed from the routes during this analysis.

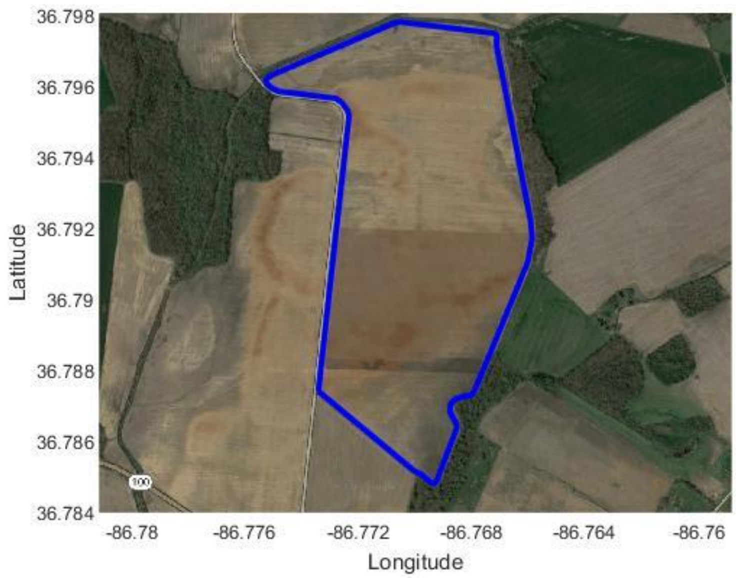


Figure 4-2. Field in Logan County, Kentucky where vehicle routes were recorded during anhydrous ammonia application

4.3.1 Recording Routes Driven by Human Operators

The farming operation used as the basis for most of this experiment was mowing of harvested, standing corn stalks using a rotary mower. This operation was performed using three tractors that pulled 4.57 m wide rotary mowers. These three tractors were a John Deere 6130M, a John Deere 5100E, and a John Deere 6195R, which are referred to as machines 1, 2, and 3, respectively. All tractor drivers were experienced operators and employees of the research farm. They had driven these tractors and used these implements previously. They were also used to coordinating together in the field. During this field operation, the tractor operators were told to drive as they normally would to finish the field as quickly as possible.

Several minor changes to their normal practices were used to improve data collection during this experiment. First, a simultaneous start from the entrance of the field was enforced. In addition, all operators were told to travel at the same speed. Path recording equipment was also added to the tractors. The John Deere 6195R contained a GreenStar navigation system, so its position was recorded by logging the ISOBUS location messages generated by the navigation system using a Vector GL1000 CAN datalogger (Stuttgart, Germany). The John Deere 6130M and John Deere 5100E lacked built-in navigation systems, so Trimble E-Z Guide 500 Lightbar Guidance Systems

(Sunnyvale, California) were used to record their paths. Before starting, the navigation systems in all tractors were set to an identical A-B line. While setting the same A-B line is standard practice for coordinating the work of multiple tractors in the same field, it also ensured overlap between rows was consistent during the experiment and did not cause field efficiency differences.

The tractors used on the Logan county farm for anhydrous ammonia were all heavy-duty class Case IH tractors with power ratings of 350 kW (470 horsepower) (machines 1 and 2) and 335 kW (450 horsepower) (machine 3). All three tractors used ISOBUS and auto-guidance technology from Case's Advanced Farming System (AFS) which enabled logging vehicle position by logging ISOBUS traffic. The implement width was 19 m. The tractor operators were all experienced operators at using this equipment, working together, and performing anhydrous ammonia application. The operators performed this operation as normal and made no adjustments for the data collection in this experiment.

4.3.2 Optimized Routes Generation

4.3.2.1 Convert Field to Model Representation

The first step in generating computer-optimized routes was creating a digital representation of the field paths based on the human-driven paths. In the digital representation, the field paths were represented by their endpoints. Rather than directly using the human driven paths with their inaccuracies, these paths were adjusted to match perfectly the 4.57 m or 19 m implement width used in creating the A-B lines that initially guided the drivers. The endpoints and midpoints of these paths were used at VRP nodes following the procedures in Seyyedhasani and Dvorak (2017). These steps provided the digital representation of the field as VRP nodes, and the next step was to assign costs of the connections between nodes.

Kinematic characteristics of the combination of the vehicle and implement were determined from the original human-generated routes to produce the cost matrix for the model. The turning radius for the vehicle and implement combination was more than half of the working width ($r > w/2$), so "bulb" and "hook" turns were required to steer into adjacent paths (using terminology from Jin and Tang (2010)). With these turns, vehicles start to diverge towards the opposite direction to provide more space for turning. The hook turn was used when the machine travel direction, θ, was not perpendicular to the headland direction, φ, and the "bulb" turn otherwise (Figure 4-3). As other researchers (Jin & Tang, 2010) have already worked on the mathematics of different types of turns, in this work, we employed the empirical data corresponding to these turns to calibrate the computer model.

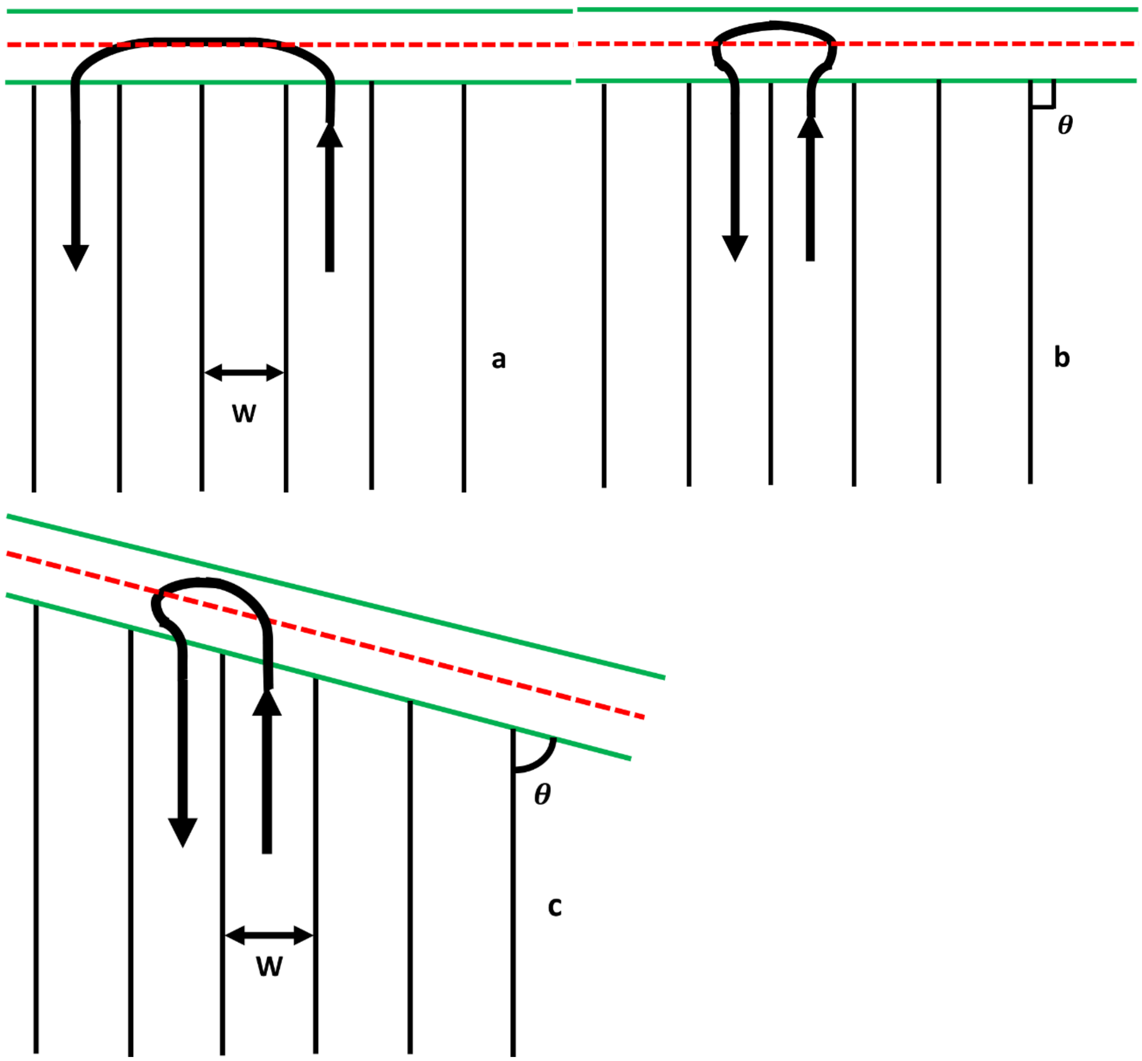


Figure 4-3. Different type of turns used in the simulation a) "flat" turn, b) "bulb" turn, and c) "hook" turn. The red dashed line represents the turning trail.

The "flat" type turn was employed for turns into non-adjacent paths (i.e. skipping one or more paths) as this path arrangement provided sufficient space to turn (Jin & Tang, 2010). A turning trail inside the headland was designed, surrounding the boundary, to connect each pair of the paths. To determine the length of the "flat" turn between each pair of paths, a and b, corner lengths were added to the travelling length on the turning trail, i.e., $flatTurnLength_{ab} \ = 2 \times \frac{1}{4}(2\pi r) + \text{travelLength}_{ab}$ (Figure 4-4). The turning trail provided a path around the entire field. This enabled using the equation for the flat turn to calculate turning and non-working travel times even if subsequent paths were not on the same headland segment. The variable, travelLength_{ab}, merely incorporated the travel time between the paths using segments of the turning trail, and the flat turn equation then provided the time required to transition between the working paths and the turning trail.

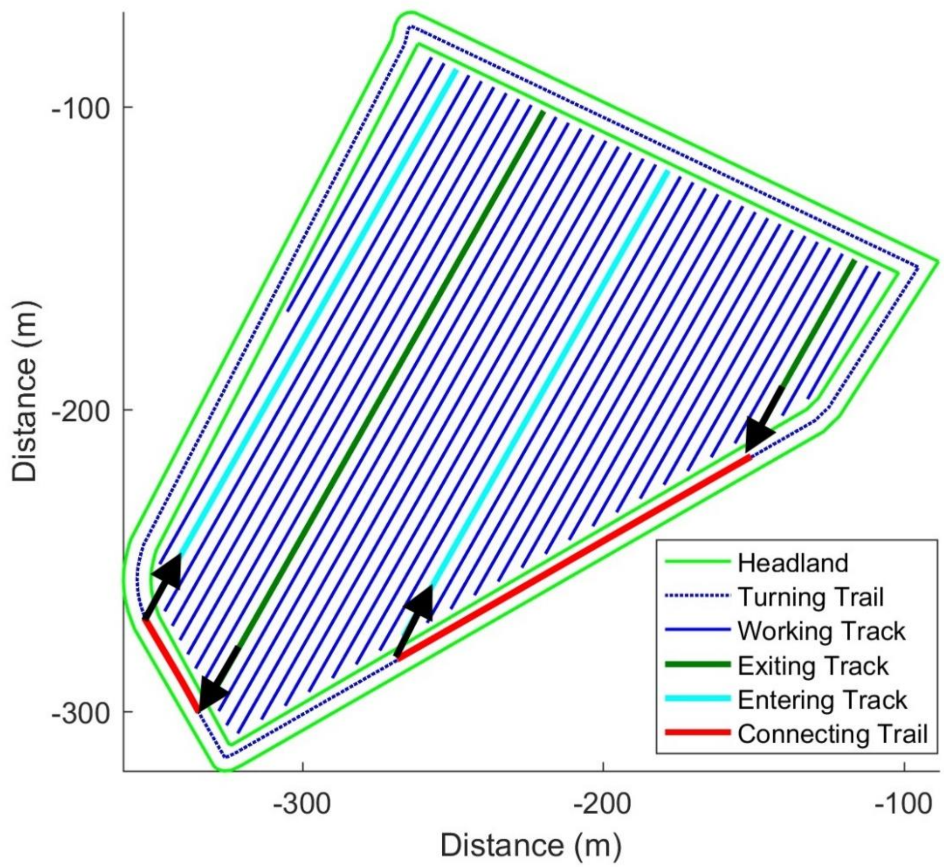


Figure 4-4. Track type designations for two example turns with non-adjacent working paths.

In many cases, turning is a challenge for vehicles taking “bulb” or “hook” turns; however, the turning speed recorded during this experiment was not significantly different from working speed, i.e. 7.55 and 7.54 km h^{-1}, respectively. The non-working travel speed, 7.57 km h^{-1}, was also nearly identical to working and turning speeds. Non-working travel was very limited in the routes created by the tractor drivers, so the drivers did not adjust speed in these limited non-working periods. Therefore, the model was created assuming equal speed for non-working, working, and turning travel speeds. As such, in developing a cost matrix (for optimization) and transformation matrix (to determine the amount of time for traveling from the physical location of each node to other node's) travel speeds were set at a constant of 7.5 km h^{-1}. This was not true, however, as to the Logan county operation. Each vehicle operated at a different velocity, 8.52, 8.17, and 7.28 km h^{-1}, for the Machine 1, 2, and 3, respectively. Hence a cost matrix with a more complex data structure was developed to calculate the transformation matrix for each machine individually, and address the kinematically heterogeneous fleet.

4.3.2.2 Creating computer-optimized routes

Computer-optimized routes were only generated for the rotary mowing operation on the C. Oran Little Research Farm since this was the only farm where repeated operations were conducted. The goal of the optimization procedure was to minimize a fitness function including both total driving time and the time required for the slowest vehicle to finish as described in Seyyedhasani and Dvorak (2017). An initial solution for the computer-generated routes was obtained using a modified version of the Clarke-Wright algorithm. This solution was improved with further processing through Tabu Search, a high-level meta-heuristic procedure. The Tabu Search algorithm was repeated until one iteration had passed with no improvement (Figure 4-5). At this point, the optimization program halted and provided its best solution (so far) as the optimized routings. As a meta-heuristic procedure, Tabu Search cannot be guaranteed to produce the global optimal solution. It is also likely that further iterations could further optimize the solution. However, the solution generated by this procedure already predicted a significant decrease in work time compared to the routes used by the human tractor drivers so the optimization procedure was halted at this point and the new routes were used for testing in the field.

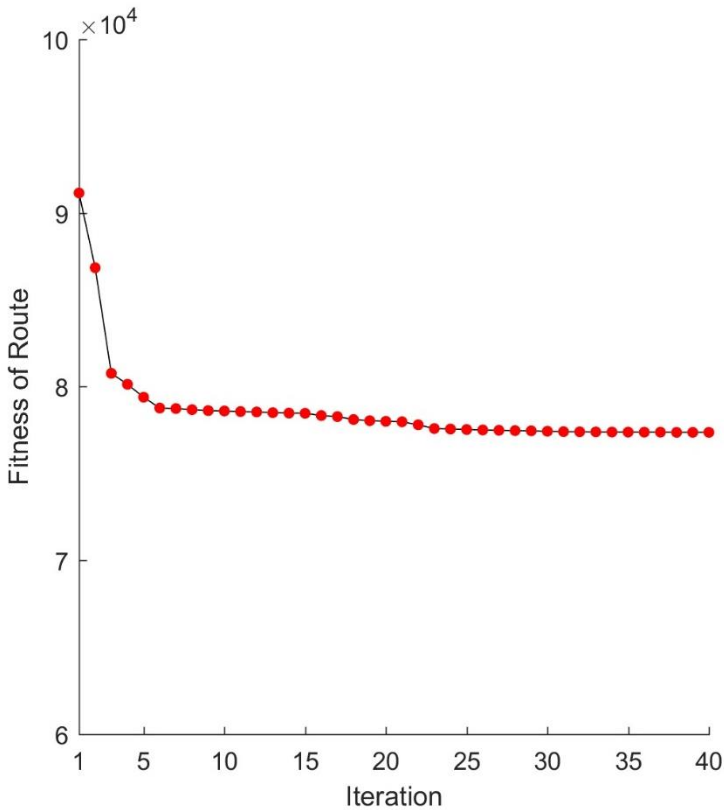


Figure 4-5. Fitness of routes at each iteration of the Tabu Search optimization procedure.

4.3.3 Using Optimized Routes in Field

After generating the simulation-based routes, the operation was repeated to verify the feasibility of the allocated routes as well as the accuracy of the model predictions in terms of the field completion time. The navigation systems in the available tractors were not capable of displaying path sequence information to help the drivers follow the optimized route sequence. Therefore, sequencing had to be performed by a second person riding with the tractor driver. This person tracked route progress and communicated with the driver to ensure the tractor travelled down the appropriate paths at all times. One tractor (machine 3 from before) was used to follow all three machine routes. It started with the route for machine one, and then proceeded to the routes for machines two and three. This use of one machine ensured that the optimized routes were all followed with the same degree of accuracy as the same navigator and driver handled all routing. This was important, as following routes in the patterns generated by the computer optimization was not standard practice for these tractor operators.

The repetition of this field operation occurred two weeks after the original operation and under similar ground and weather conditions. Unfortunately, a perfect replication was not possible, as the original mowing operation had cut down the standing corn stalks. This change enabled the tractor in this second trip through the field to achieve a higher average travel speed than the tractors in the first trip (8.6 km h^{-1} compared to 7.5 km h^{-1}). To ensure fair comparisons, the travel times in the second trip were increased by 14% to reflect the differences in average travel speed. The actual recorded times are provided in the results section, but all analysis and comparisons were done with the times adjusted for equal travel speeds of 7.5 km h^{-1}.

4.4 RESULTS

4.4.1 Cost Matrix Travel Time Verification

The routes driven by the human operators during the anhydrous ammonia application operation in Logan County, Kentucky (Figure 4-6) were divided into ten sub-routes. These ten routes were randomly created with each route incorporating a variable number of field passes (Figure 4-7). The routes driven by the humans were not the perfect routes used in creating the time estimates with the cost model. For example, the driven routes do not perfectly utilize the bulb, flat and hook turns used in creating the cost matrix. This is illustrated by the “extra” driving that occurred at the end of some rows.

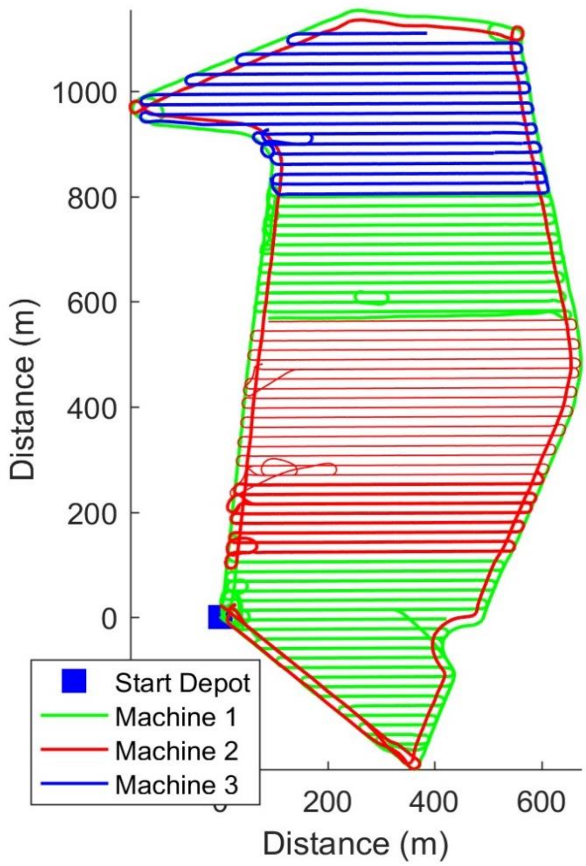


Figure 4-6. Recorded routes driven by human operators during the anhydrous ammonia application operation in Logan County, Kentucky.

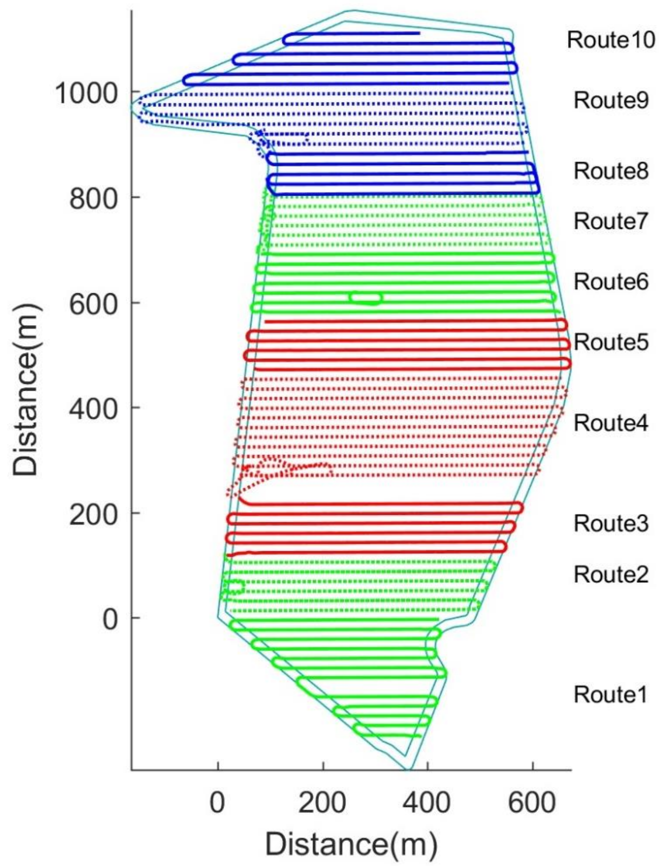


Figure 4-7. The routes in the field were divided into 10 smaller routes.

For each section of the routes, the error between the actual times recorded by the loggers for travel along that path and the time predicted by the cost matrix for that same route was between -6% and 6% with most estimation times within 5% of the actual measured times (Figure 4-8). The Root Mean Square Error (RMSE) was only 3.9 seconds. Although the drivers did deviate from the perfect routes used in creating the cost matrix, the overall error in travel time estimation was minimal. This illustrates that the time estimates from the vehicle travel model closely match the real-world times.

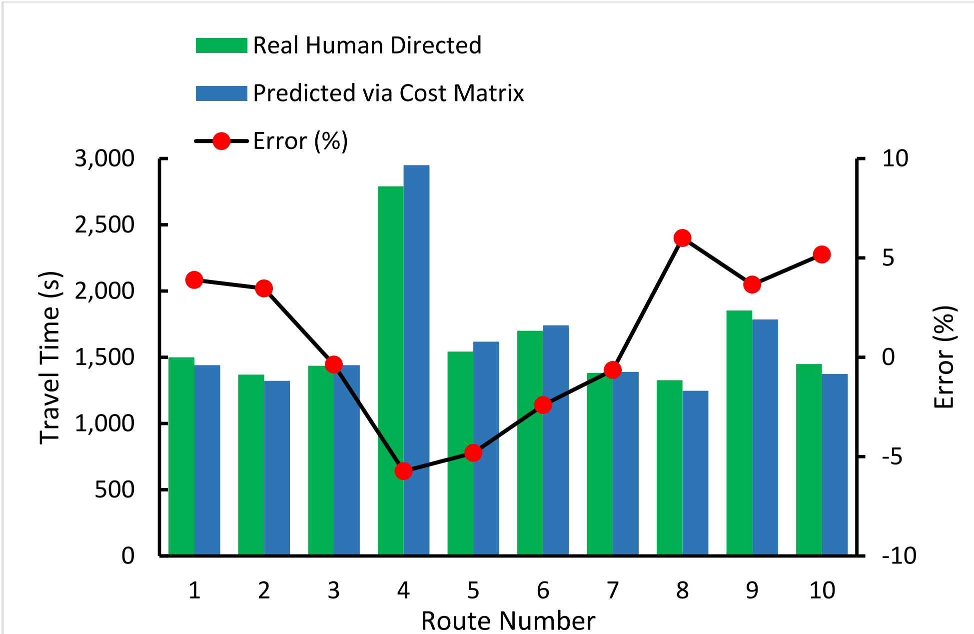


Figure 4-8. Comparison of recorded travel times to times estimated by the cost matrix for the same route.

4.4.2 Route Optimization Verification

Using the optimized routes from the computer model, the time to complete the field work was reduced from 122 to 101 minutes (Table 4-1), a reduction of 17.3%. In addition to reducing completion time, the total time for all tractors combined was reduced from 340 to 301 minutes, a 11.5% reduction. These reductions illustrate the ability of the route optimization procedure to improve field work parameters, improving the field efficiency and effective field capacity by nearly 12% and 21%, respectively. Table 1 also confirms that the computer model could accurately estimate vehicle travel. The model predicted a total time of 309 minutes and a completion time of 103 minutes, both of which were within 2% of the actual times when tractors followed those routes in the field.

Table 4-1. Field completion time and total time of field work of the rotary mower experiment

Multi-Field Experiment	Total Time (min)	Completion Time (min)	Field Efficiency (%)	Effective Field Capacity (ha h^{-1})	Vehicle Velocity (km h^{-1})
Human-Directed Routing	340	122	82	7.67	7.5
Simulated Optimized Routing	309	103	91	9.09	7.5
In-Field Optimized Routing	301	101	92	9.27	7.5

The original tractor routes driven by human operators were reasonable and demonstrate the proficiency of the drivers in managing route allocation (Figure 4-9). While the routes predominately resemble a "work zone" approach, individual "work zones" were not rigidly enforced as the drivers attempted to minimize non-working time. Machines 2 and 3 begin working at the start location with machine 2 working on the outer border and machine 3 starting with the inner border. Machine 2 follows the outer border to the far side of the field *a* and starts on the smaller triangular section of that field, while machine 3 completes the section of field *a* closest to the starting point before proceeding to the smaller field *b*. When machine 2 finishes the small triangular section of field *a*, it moves to the far end of field *a* and starts working toward machine 1, which began working in the middle section of field *a*. When machines 1 and 2 finish field *a*, they move to field *b* to help machine 3 finish it. The shifts of machines from the one end of the field to the far away regions created non-working travels which adversely affected the field efficiency. In these original routes, each vehicle was used for approximately the same amount of time. Machines 1, 2, and 3 operated for 122.0, 103.7, and 114.3 min, respectively, for a total operating time of 340.0 minutes. Working speed was 7.5 km h^{-1}.

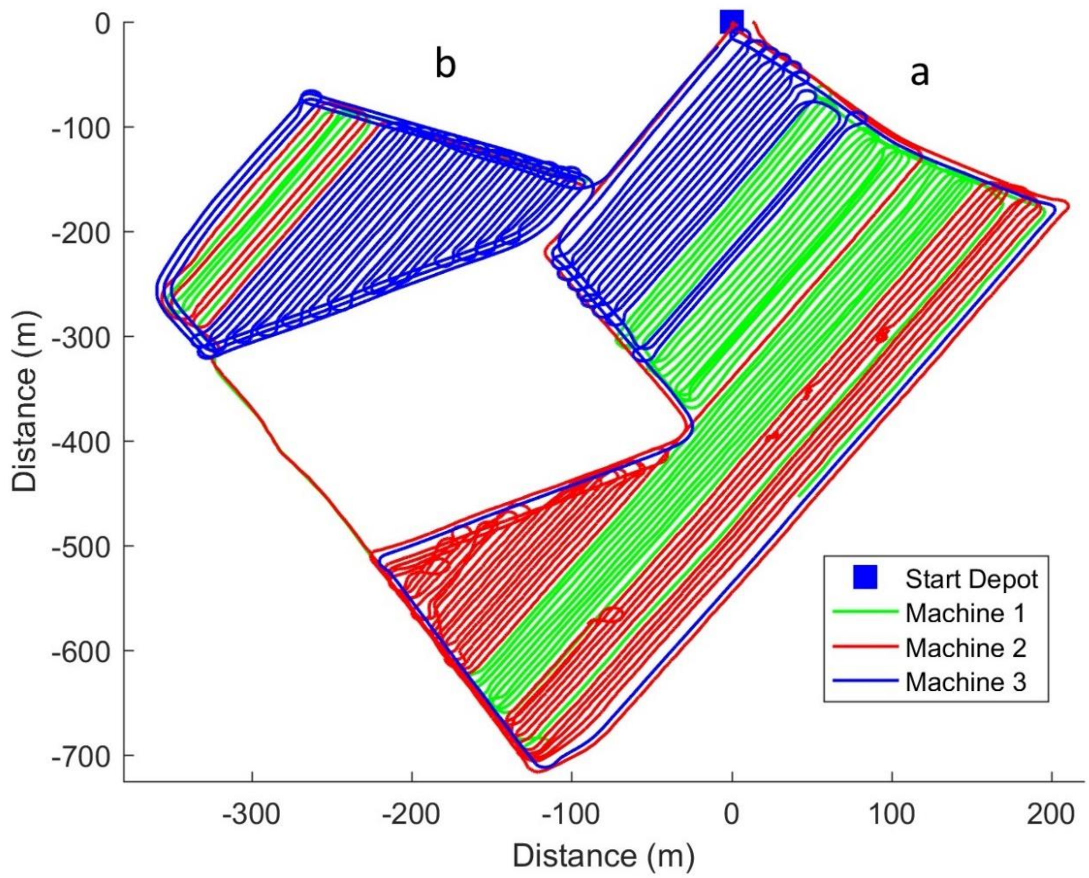


Figure 4-9. Original routes of the tractor drivers during the rotary mowing operation.

The routes generated by the VRP optimization procedure (Figure 4-10) provided an estimated 15% reduction in completion time from 122 to 103 minutes. Each machine was predicted to complete its route in 103 minutes as the optimization evenly distributed the work. Total travel time was expected to drop by 9% from 340 to 309 minutes. As such the field efficiency as a parameter directly impacted by the total travel time improved as much. When looking at the computer-optimized routing, the VRP optimization procedure adopted time-reduction strategies like those used by the tractor drivers to take advantage of field shape peculiarities. Like the human drivers, one machine worked the triangular section at the far side of field *a*. Another machine was responsible for field *b*, and the last machine worked the large middle section of field *a*. However, unlike the human drivers, the optimized routes produced by the computer used only one machine in field *b*. Also, the routes were more evenly distributed to ensure that all machines finished at the same time.

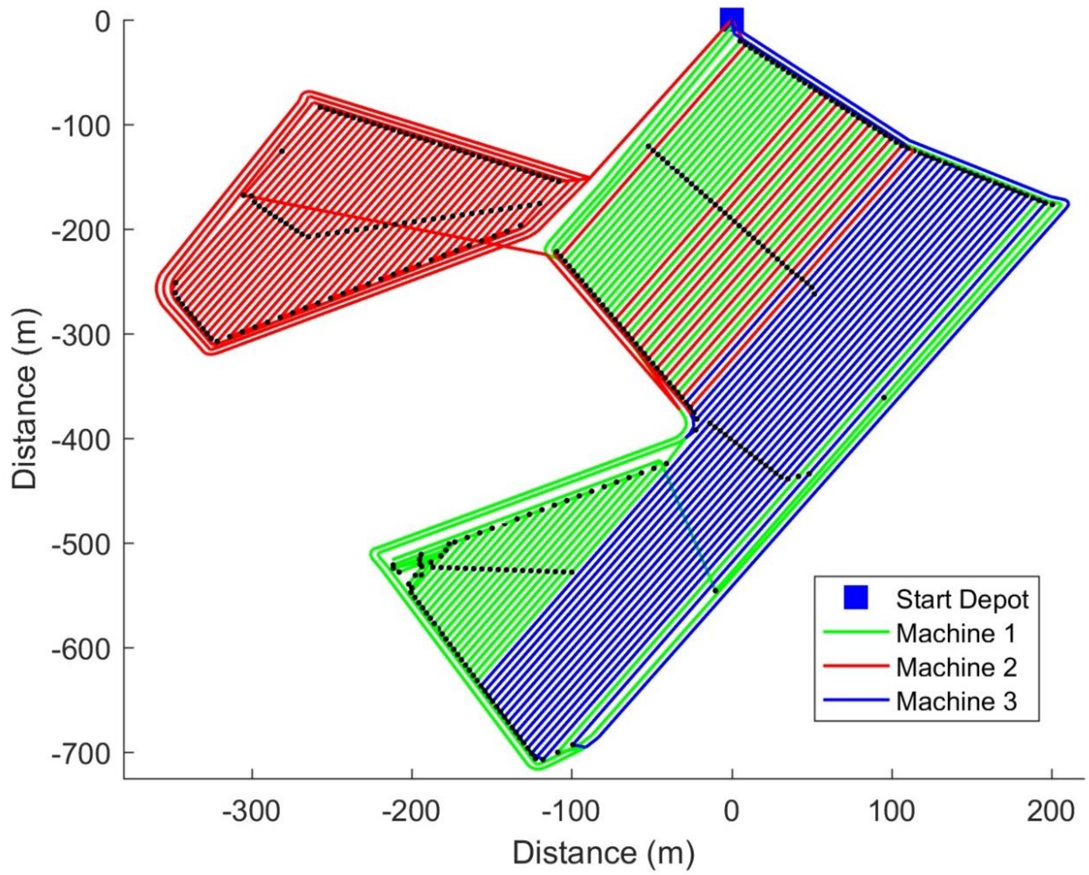


Figure 4-10. Routing provided by the VRP optimization. The black dots represent the VRP nodes placed at the endpoints and midpoints of each field path.

When the optimized routes were followed by a human driver (Figure 4-11), the predicted completion and total working time reductions were realized. Since the tractor was following these routes in a field that had already been worked, its travel speed was faster than before, at 8.6 km h^{-1}, and operating times for machines 1, 2 and 3 were 85, 88, and 86 minutes. After adjusting travel times to reflect the same 7.5 km h^{-1} average working speed of the original operation, the total time accounted for 297 minutes and the length of time for machines 1, 2 and 3 was determined to be 97, 101, and 99 minutes, respectively. Another time adjustment is necessary for missing passes in the corner of the triangular section of field (visible in Figure 4-11). These were supposed to be completed by machine 1. Given the working and travel speeds of machine 1, these missing routes would have required two minutes each, so four minutes were added to machine 1's time.

Therefore, the resulting total time was 301 minutes with machine 1 requiring 101 minutes (as shown in Table 4-1), and as such the effective field capacity was calculated to be 9.27 ha h^{-1}. The adjusted operating times and completion times are within 2% of the times predicted by the computer model of the field operation.

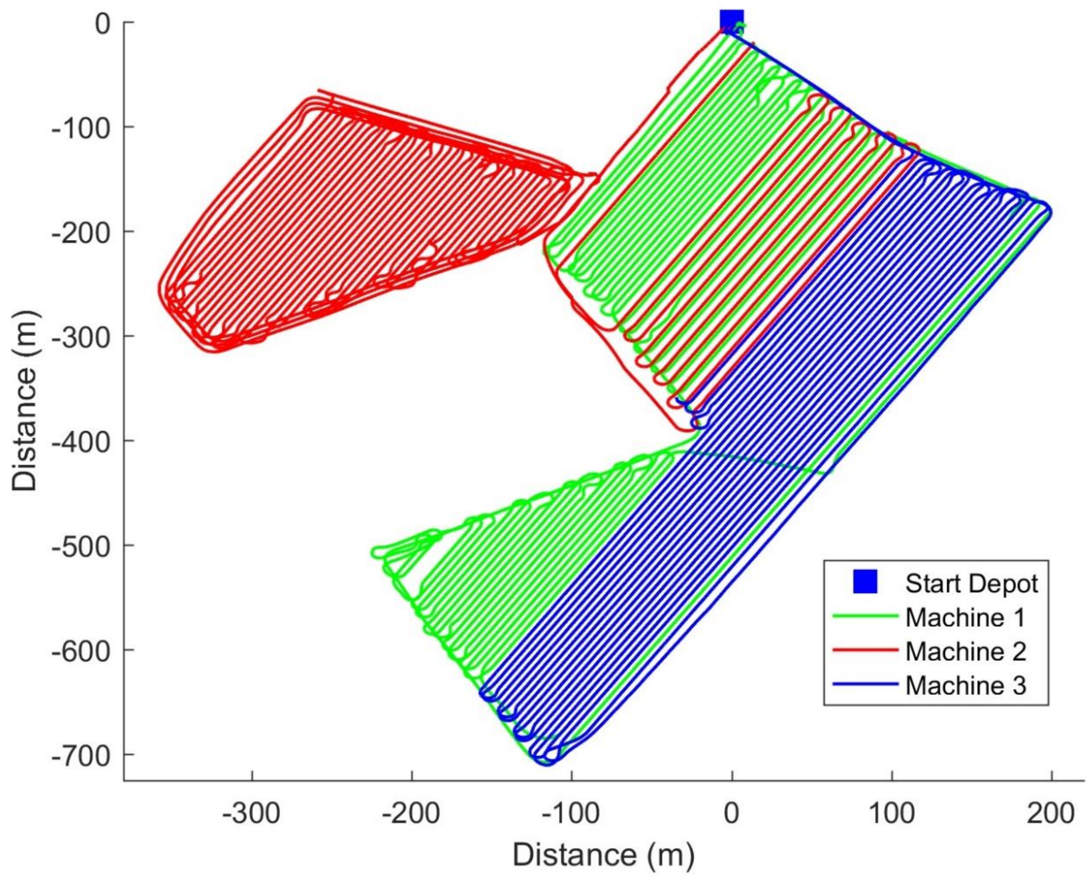


Figure 4-11. Travel paths of a human driver following the optimized routes.

The confirmation of reductions in field completion time indicate the potential of this type of technology if it were incorporated within current tractor navigation systems or utilized in routing future autonomous agricultural machines. As implemented within this testing, on-farm use of this technology is infeasible, as it required a careful digital depiction of the field geometry and paths, information on vehicle dynamics, offline optimization and a navigator riding with the tractor driver to ensure the path was followed correctly. However, future navigation systems could easily include route indicators and help drivers follow more complex optimized routes. In addition, farm management systems often include geometric representations of fields and a history of previous field operations. This information could be used to generate paths and to determine the vehicle dynamics when a similar operation was last performed. Appropriately integrating these information systems would quickly enable producers to achieve the efficiency gains provided by this optimization.

4.4.3 Conclusions

One outcome of this project was proof that this computer model can accurately represent field working times of different routings. When the tractor driver followed the optimized routings provided by the model, the field completion time estimated by the model was within 2% of that measured in the field. Another outcome was the confirmation that computer optimized routings can result in a reduction in both time to complete the field and the total operating time of the vehicles. Even though time reductions and accuracy of using computer generated routes have been already reported in literature, this work was focused on path planning of a distributed fleet of vehicles, along with routing those vehicles. Other reported work has focused on different applications within agriculture such as master-slave systems (S. G. Vougioukas, 2012) or focused on the creation of guidance lines (I. A. Hameed et al., 2010). The time required to complete the field dropped by 17.3% from 122 minutes to 101 minutes, while the total operating time for all vehicles decreased by 11.5% from 340 minutes to 301 minutes. These reductions are at levels that provide a significant impact on producer's operations and illustrate the ability of computer-optimization to provide important benefits to producers.

CHAPTER 5: OBJECTIVE 4: FIELD LOGISTICS SIMULATION COMPARING FIELD EFFICIENCY AND FIELD CAPACITIES BETWEEN LARGER AND SMALLER EQUIPMENT

5.1 SUMMARY

Deploying multiple vehicles, as opposed to an individual large vehicle, to complete a given agricultural operation is a way to improve effective field capacity. Using multiple smaller machines will mitigate the risk of soil compaction and provides more flexibility in machinery management, compared to utilizing a single larger machine. In this work, comparison of field work efficiencies was performed when a single larger machine is replaced with a number of smaller machines of the same total size. To that end, the task of a single machine in three real-world fields was converted and assigned to two small machines and three smaller machines. Initial path allocation and path scheduling for the involved vehicles was obtained through a modified version of Clarke-Wright saving method. Then, the solutions were post-processed by the meta-heuristic Tabu Search procedure to improve the results. In all three fields that were investigated the time to complete the field work was reduced, by up to 11%, when replacing a single vehicle with a number of smaller vehicles to carry out the same operation. Results of the method demonstrated consistent improvements for the effective field capacity (by up to 16%) and field efficiency (by up to 9.5%) when a larger machine was replaced with multiple equivalent smaller machines. These reductions highlighted the importance of considering multiple small vehicles in order to conduct agricultural operations.

5.2 INTRODUCTION

One of the common and frequently used approaches in improving effective field capacity is using a single vehicle with faster speed and bigger size and width, i.e. higher throughput. Even though this approach is more intuitive and popular among farmers, there are several impediments to the use of larger and faster agricultural machinery. Soil compaction by large, heavy machinery is one concern (Blackmore et al., 2002; Hamza & Anderson, 2005). The soil compaction associated with mechanized farm operations is characterized by the decrease in soil porosity underneath the wheel and the formation of ruts at the soil surface. As such, the degree of the compaction depends directly on the axel loadings, tire dimensions, and the velocity of a vehicle (Lebert, Burger, & Horn, 1989). This is true even in no-till systems, as in a single pass with a planter more that 30% of the coverage area can be affected by machinery travel (Tullberg, 1990). Heavy machinery can also cause subsoil compaction in addition to compaction of the top soil (Raper, Reeves, & Burt, 1998).

When focusing on economies of scale, one large vehicle is often cheaper than multiple smaller ones. However, obsolescence can impact newer technologies, and as such, the vehicle life with newer machines can be adversely affected (Shearer et al., 2010b). Additionally, the long-term historical focus on improving field capacity through the use of larger and faster machines means that one cannot expect substantial further improvements in effectiveness of modern, bigger and faster agricultural machinery (Dionysis D Bochtis et al., 2014). Smaller machines could also potentially see advantages in the economies of scale during manufacturing as the largest agricultural machines are currently only produced in limited quantities.

Even though deploying large equipment requires less labor, sometimes this approach places farmers in a quandary. Smaller and complex fields are difficult to farm with large implements. One of the largest (widest working width) pieces of modern agricultural machinery is the sprayer. Luck, Zandonadi, Luck, and Shearer (2010) using a sprayer with a 24.8 m boom width in a wide range of field shapes and sizes found 12.4% over-application on average. The larger equipment creates off-rate application errors as the velocity, pressure, and height variations increase across the wider booms. Relying on a single large piece of equipment means that there will be less redundancy in the case of equipment failure (Blackmore et al., 2002).

The other method of improving the effective field capacity is to increase the number of machines being used at one time, which is common on most large-scale farms around the world (Blackmore et al., 2002; Shearer et al., 2010a). Traditionally, this is used by producers looking for greater field capacity than that provided by a single unit of the largest machines. However, using multiple machines allows the use of smaller machines with less compaction risk. It also provides redundancy in the event of an equipment failure and more flexibility in machinery management. In many situations, using multiple smaller vehicles in the same environment is a good strategy to handle very irregular shaped or small fields. And another significant benefit of smaller machines will be the ability of manufacturers and producers to manage the liability of fully autonomous machines (Blackmore et al., 2002; Jones, 2014). However, there are a number of issues associated with the use of multiple smaller machines performing the same operation—labor cost and logistics.

Currently, reducing labor costs has been a primary driver of the move toward larger equipment. Typically, one operator is required for each machine performing agricultural tasks, and using more machines requires more people. However, modern advances in sensing, information, and communication technologies have paved the way for fully autonomous vehicles. Noguchi, Will, Reid, and Zhang (2004) developed algorithms for a master-slave multi-robot system performing farm operations. Control of the master vehicle is manual and the autonomous slave vehicle follows the master. S. Vougioukas (2009) put forward a master-slave method for more than two vehicles. In his proposal a team of robots as slaves would be coordinated through the motion characteristics specified by the master one. According to simulations, the method verifies the ability to coordinate the motion of a fleet of robots, even though no experiments are implemented with the proposed method. The concept of master-slave multi-robot can be employed for particular agricultural operations such as grain harvesting in which at least two machines are required to work in a coordinated fashion. The ability to manage the whole operation by only one operator from the master machine, i.e. the harvester, would reduce the labor cost significantly.

Johnson et al. (2009) designed behavior and actions for a team of three tractors to perform harvest operation of peat moss. The team carried out approximately 100 field test harvesting missions during one season. To accomplish mission, commanding and monitoring was done remotely by a human operator as a team leader. Further, a large European project, Robot Fleets for Highly Effective Agriculture and Forestry Management, has specifically focused on the development of a fleet of robots capable of autonomous weeding tasks (Emmi et al., 2013). Based on current research, the next generation of autonomous agricultural machinery could be designed with robust control systems that enable reducing the number of operators from one for each vehicle to one remotely for all the vehicles accomplishing the same task in a collective fashion. These technologies also will bring about a “paradigm shift” in the size of field machinery, according to Shearer et al. (2010a).

Although the development of unmanned agricultural machines could remove the labor constraint on using multiple machines, logistics is still an issue to consider with the use of multiple vehicles. Deployment of multiple vehicles in the same area increases the chance of collision, as S. G. Vougioukas (2012) explored through the coordination of a team of autonomous agricultural vehicles in master-salve and peer-to-peer modes. A team of experienced human operators working together are capable of developing routes for machines that are reasonably efficient and avoid collisions. Removing these operators through automation may reduce the labor costs, but it requires that the new machines be capable of solving these logistic challenges through algorithms. Several algorithms have been proposed for this routing challenge and many are based on the classic computer science problem, the Vehicle Routing Problem (Johnson et al., 2009).

All thing considered, replacing a larger machine with a number of smaller machines seems to be capable of removing most of the drawbacks of utilizing large machines to improve effective field capacity. In this paper, we will study the field logistics of a larger machine and a number of smaller ones in terms of effective field capacity and field efficiency through simulations.

5.3 MATERIALS AND METHODS

Looking at a field as a system to investigate the characteristics of deploying a single larger vehicle or a number of smaller ones, it is rational to replace a single larger vehicle with multiple smaller ones. To conduct a field operation, the principle difference between a big machine and small one is the power to operate larger implements. That is, the primary operational difference is implement width. Hence, to carry out this work, a number of steps were taken. In the first step, working paths of the test fields were generated according to the implement width for a variety of machine sizes. In the next step, the field paths were assigned and scheduled to the available vehicles. For each field, the number of vehicles multiplied by the width of the implement was a constant so theoretical field capacity was identical. Finally, the resulting field work scenarios were evaluated for field efficiency and field capacity.

5.3.1 Task Conversion

Field conversion for deploying a number of small vehicles fundamentally requires re-generation of field paths according to the size of utilized vehicles. This, in the first step, necessitates preserving field properties including geographical position, boundary, and the assigned headland layout of the field, in addition to path characteristics such as direction and paths pattern. Then the field paths should be re-generated so the entire field is treated without overlap using the new implement widths.

5.3.2 Machinery Operation Parameters of Interest

The Effective Field Capacity (EFC) and Field Efficiency (FE) are the parameters of interest to producers. As such, the comparison of vehicle replacement is performed with respect to these parameters. EFC represents how much land area is worked in a specific period of time (D. D. Bochtis & Sørensen, 2009; Seyyedhasani & Dvorak, 2017). It varies depending on operating conditions and field shape and size. Factors that adjust operating speed (conditions) or change non-working time (field shape) will create differences in time requirements without changing the land area that is ultimately worked. When EFC is considered at the field scale, it can be calculated as

(5.1)

$$\text{EFC} = \frac{area_{field}}{time_{last}}$$

where EFC is the land area that is worked in a given period of time (ha h^{-1}), $area_{field}$ is the area of the field (ha), and $time_{last}$ is the time required to finish the field (h).

With multiple machines that all start at the same time, $time_{last}$ becomes the time required for the final machine to finish its work in the field. As equation (5.1) demonstrates, improving effective field capacity requires reducing the field completion time.

FE is another vital field performance parameter. It is the ratio between the machine productivity in actual field conditions and the theoretical maximum machine productivity (American Society of Agricultural and Biological Engineers, 2011). Maximum productivity assumes a machine is constantly engaged at maximum speed and utilizing the full width of the implement. Productivity in actual field conditions is reduced by the non-working time required to turn in headlands in addition to other issues. As with EFC, FE is affected by operating conditions and field shape characteristics. FE can also be determined based on the ratio of the time a machine operates at maximum productivity to the total time required to complete a field operation (American Society of Agricultural and Biological Engineers, 2011). When considered at the field level with multiple machines, FE can be calculated as

(5.2)

$$\mathrm{FE} = \frac{time_{all,theoratical}}{time_{all}}$$

Where FE is field efficiency (expressed without units as a ratio), $time_{all,theoratical}$ is the amount of time it would take to work an area of the same size as the field assuming all machines were operating continuously at maximum productivity (h), and $time_{all,}$ is the total amount of time all the machines actually had to work to complete the field (h).

As such, decreasing the total machine work time in the field will result in increasing the field efficiency. It is possible to calculate the times required by the FE equation based on vehicle travel routes using vehicle routing notation as:

(5.3)

$$time_{all,theortical} = \sum_{a \in N} \sum_{b \in N | b > a} c_{ab}\, k_{ab}$$

and

(5.4)

$$time_{all} = \sum_{a \in N} \sum_{b \in N} c_{ab} x_{ab}$$

Where N is the set of all points (or nodes) defining the ends of all paths (working and non-working for all vehicles) in the field, a and b are points defining the ends of field paths (for working paths, these can be considered the points A and B in A-B lines; for non-working paths, this is A and B points on different A-B lines), c_{ab} is the time required to work between points a and b (h), x_{ab} is 1 if that path travelled from point a to b

appears in the route assigned to a vehicle and k_{ab} is 1 if the path traveled between nodes a and b by vehicles is a working path and 0 for non-working paths.

Improvement of EFC and FE for any specific field operation is contingent upon reducing $time_{last}$ and $time_{all}$ respectively.

5.3.3 Experiment Design

5.3.3.1 Test Conditions

Three different fields were selected with differences in shape, size and complexity. One field was a test field used as an example in path planning research. For this field, the working paths follow the layout determined by I. A. Hameed et al. (2011) to be optimal. The other two fields are located in Kentucky, USA and the working paths are based on actual tractor driving paths recorded using fleet telematics equipment. The recorded paths (or suggested optimal paths) were used to create the single vehicle scenario. Then additional test scenarios were created with two and three machines replacing the single machine. In the scenarios, all machines were considered to operate at the same speed, and the implement widths for the two and three machine scenarios were one-half and one-third, respectively, of the width of the implement in the one machine scenario. Thus, every scenario had the same maximum theoretical productivity and capacity.

Maintaining identical maximum theoretical capacity between scenarios enabled direct comparisons of EFC and EF. It also ensured that routes in the field could be preserved between scenarios with different implement widths. For the scenarios with implements one-half and one-third of the original widths, one or two paths, respectively, were added between the original paths. Thus, effects stemming from merely shifting paths were avoided.

The routes taken by machines while covering all of the field work paths can have a dramatic impact on field efficiency. The importance of effective routing increases as the field shapes become more complicated and the number of vehicles increases (Seyyedhasani & Dvorak, 2017). Therefore, the route optimization procedure from Seyyedhasani and Dvorak (2017) based on the Vehicle Routing Problem (VRP) was used to generate the vehicle routes in all of these scenarios. This procedure attempts to minimize both $time_{all}$ and $time_{last}$, so it incorporates a vehicle travel model used to estimate the $time_{all}$ and $time_{last}$ of any given routing procedure. This model was validated with field testing (Seyyedhasani & Dvorak, in review).

Single Field Test

This part of the experiment focuses on the common situation in which field work is being conducted in a single contiguous area. Two fields from real world farms were selected. The first field is from path planning optimization research where it was used to illustrate optimal paths (I. A. Hameed et al., 2011). It was also employed by Seyyedhasani and Dvorak (2016) to generate optimal routes for covering the entire field via different number of vehicles (1, 2, 3, 5, or 10 vehicles) through the developed model (Figure 5-1a). The field is located in the Northern part of Jutland, Denmark [56.546,9.507]. Since this field is from literature instead of recordings of actual tractor paths, it was assumed that the operation in this field was performed at 7.2 km/h in order to express results in terms of times. The field consists of 63 paths surrounded with two borders as a headland, performing the operations with a 9 m wide implement. Table 5-1 represents the geographical properties of the fields investigated.

The second field is adopted from a farm located in Russellville, Kentucky [36.793, -86.77] in which application of anhydrous ammonia has been conducted. The implement had a 19 m working width and worked at 8.2 km/h. The route followed by the driver was monitored through data loggers mounted on the vehicle's CAN bus (Figure 5-1b). Then this route was converted into a vehicle routing, node-based representation suitable for application of route optimization procedure by Seyyedhasani and Dvorak (2017).

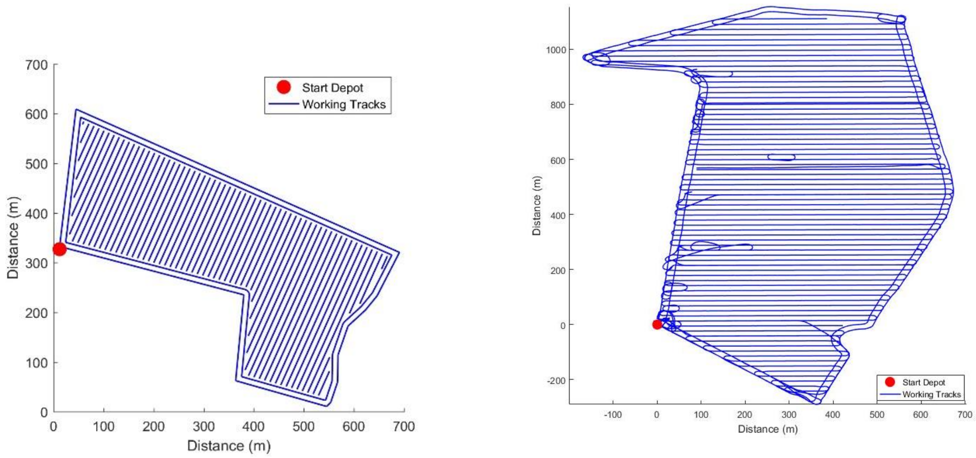


Figure 5-1. (a) Jutland field, (b) Russellville field

Multi-Field Test

The third experiment was conducted at the University of Kentucky C. Oran Little Research Center in Versailles, Kentucky [38.074,-84.737]. The task was a mowing operation of corn stalks performed at 7.5 km/h with an implement width of 4.57 m on two separate but contiguous fields. As with the Russellville field test, the operation was monitored through data loggers, and the actual driven route was converted into node-based representation for application of VRP solution methods. Figure 5-2 displays the fields in which the larger field is 12.1 ha and the smaller field is 3.5 ha.

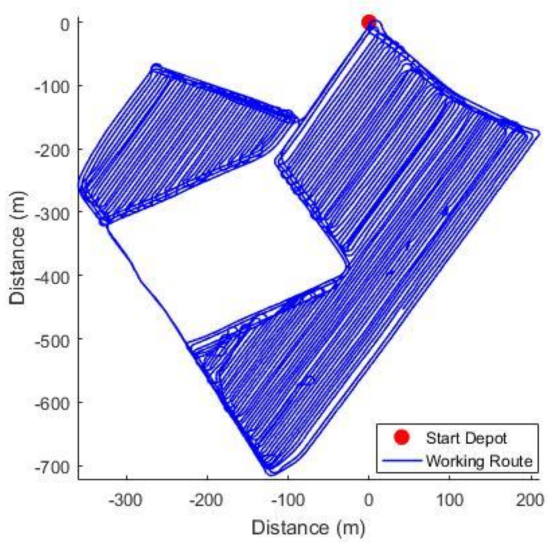


Figure 5-2. Versailles field

Table 5-1. Geographical properties of the test fields

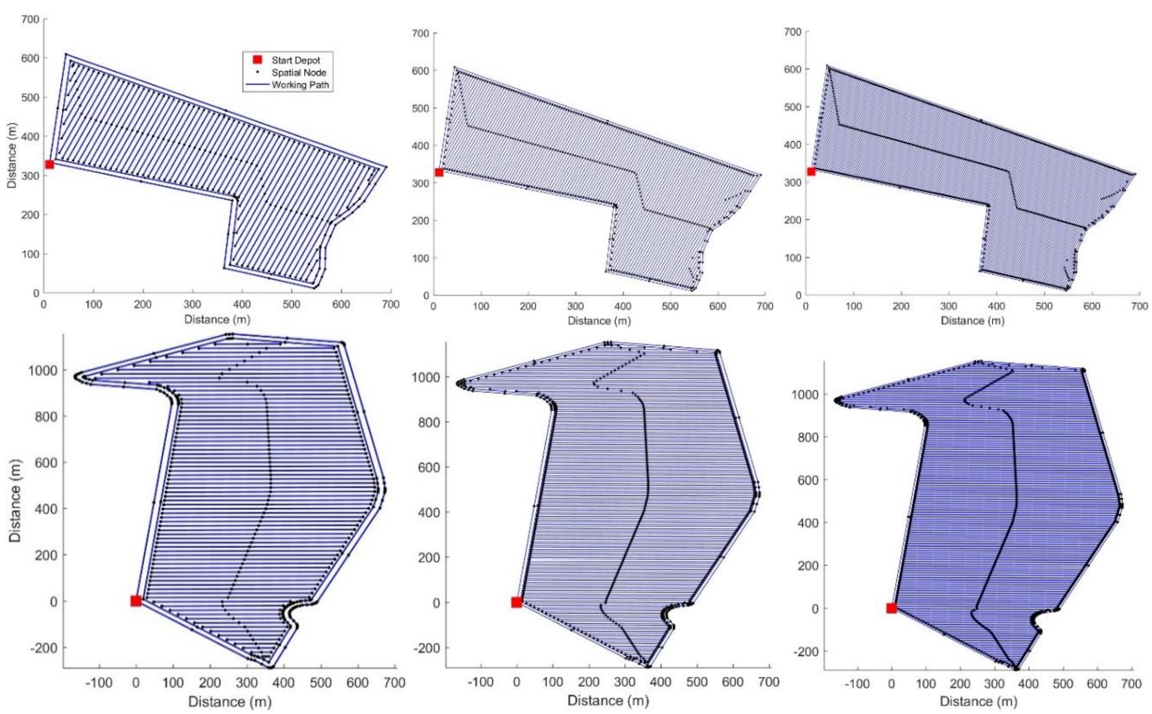
Test Field	Total Path Length (m)	Number of Paths	Longest Path (m)	Area (ha)
Jutland Field	17,250	63	707	17.2
Russellville Field	41,253	75	857	71.5
Versailles Field	35,549	119	619	15.6

5.4 RESULTS AND DISCUSSION

5.4.1 Task Conversion

The conversion of the fields created appropriate working paths for 1, 2, or 3 vehicles to operate on the same field. As shown in Figure 5-3, this conversion preserved the field characteristics and path pattern.

a b c



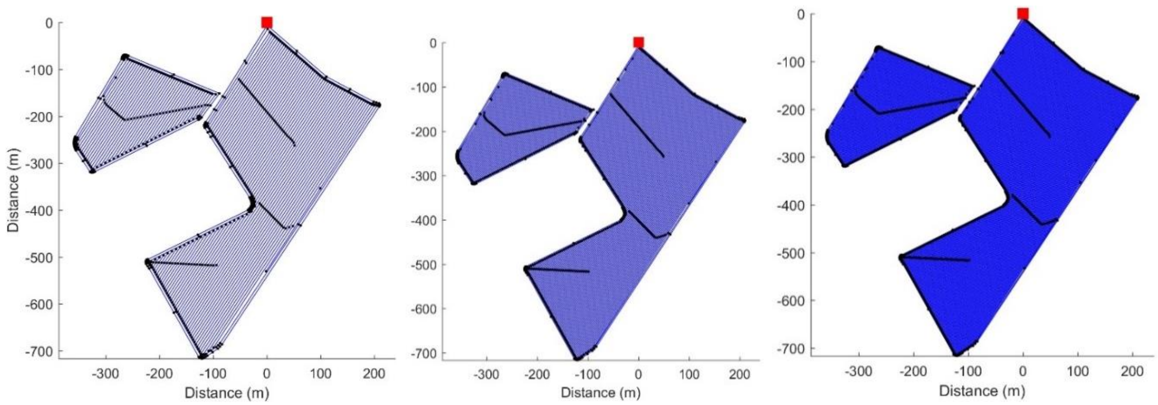


Figure 5-3. Original vehicle paths (a) re-generated to utilize (b) 2 (c) 3 smaller vehicles

Working widths and other properties of the corresponding fields are represented in Table 5-2. As demonstrated working width has reduced to one-half and one-third of the working width of the original machine. The number of paths and total length of paths did not precisely double or triple with the number of vehicles. This is due to the irregularities in field shape. To ensure field coverage with a large implement, it was at times necessary to work a path that did not utilize the full width of the implement or to continue the path for a longer distance into the headlands. The number of paths in a field is an interesting and important parameter that indicates how finely a field was divided. The original implement used in the Versailles field was smaller in relation to field size and produced more paths in comparison with the other two fields.

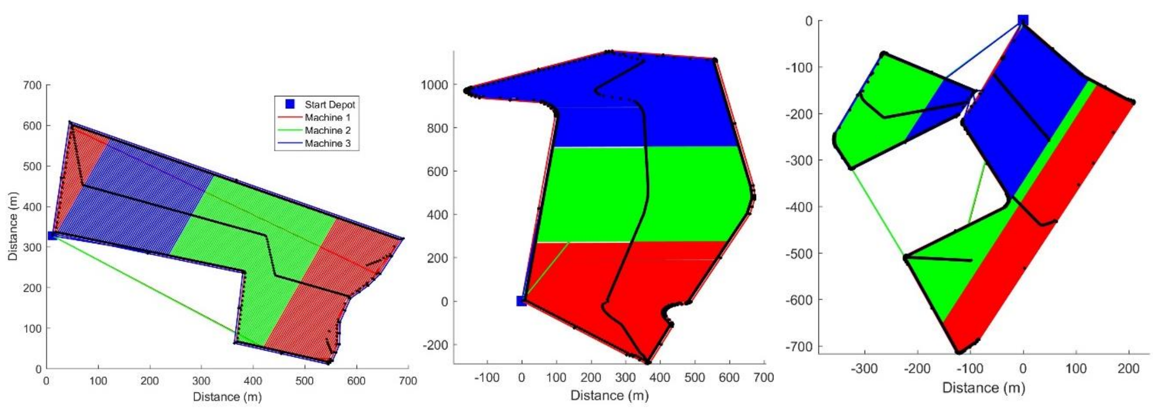
Table 5-2. Characteristic of different number of machines working together and their respective fields properties

Field	**Working Width (m)**			**Total Path Length (m)**			**Number of Paths**		
	1 Machine	2 Machines	3 Machines	1 Machine	2 Machines	3 Machines	1 Machine	2 Machines	3 Machines
Jutland, Denmark	9.00	4.50	2.25	17,250	33,475	49,674	63	130	197
Russellville, Kentucky	18.3	9.15	6.1	41,253	80,482	119,726	75	155	234
Versailles, Kentucky	4.6	2.3	1.53	35,549	69,815	103,966	119	246	372

5.4.1.1 Simulation-Based Solution

Figure 5-4 provides examples of the solutions generated when three smaller vehicles complete the operations (each color line represents one vehicle's travel). The computer procedure spawned the solutions through both the modified CW algorithm and the TS algorithm for the Jutland, Russellville, and Versailles fields. As expected, the modified Clarke-Wright algorithm closely grouped the paths assigned to each vehicle. The modified Clarke-Wright algorithm generated a solution not unlike that used by many producers today, where one vehicle sets an A-B line and provides the coordinates to the other vehicles. The drivers then try to divide the field evenly and drive to their sections, which they will work until they meet the work performed by the other drivers. Tabu Search further eliminated inefficient non-working travel and utilized border passes in the headlands to distribute vehicles to the far side of the field (Figure 5-4d-f). Also with Tabu Search, vehicles do not always proceed from one path to a contiguous path as redistributing some paths enabled a more even distribution of work (Figure 5-4e), and allowed field to be completed more quickly overall.

a **b** **c**



d **e** **f**

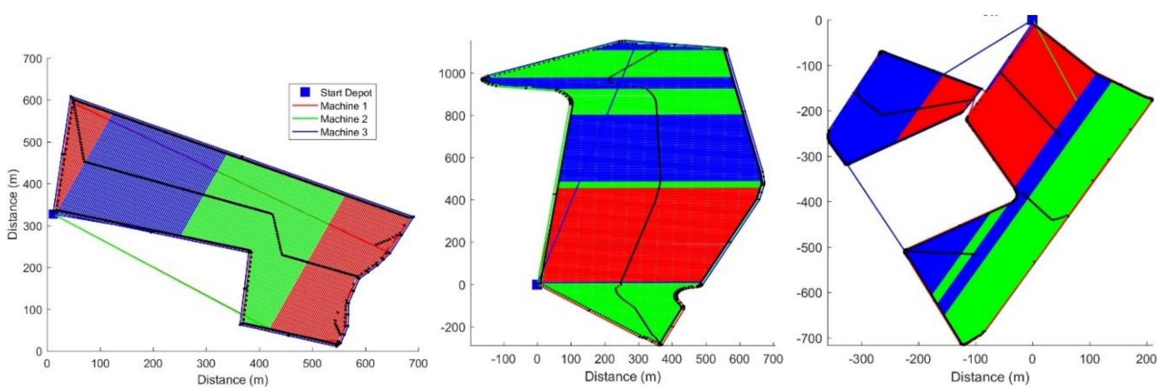


Figure 5-4. Model-based generated routes for 3 vehicles working together on the fields located in (a,d) Jutland (b,e) Russellville (c,f) Versailles. Upper row (a-c) generated by Modified Clarke-Wright algorithm and lower row (d-f) by Tabu Search procedure.

5.4.2 Field Completion Time

The completion time of the field operations always decreased or remained constant with increasing numbers of vehicles when the Tabu Search optimization was used (Figure 5-5 and Table 5-3). The less optimal routing provided by the modified Clarke-Wright algorithm did not always provide a reduction in completion time when increasing vehicle numbers. With the modified Clarke-Wright algorithm, there were continuous decreases in the Jutland and Versailles fields. However, three vehicles were fastest and two vehicles slowest in the Russellville field. This illustrates the importance of an effective route optimization algorithm if one hopes to see improvements in field completion times by increasing the number of vehicles. Final solutions provided by the Tabu Search demonstrated a continuous reduction in the field completion time as number of vehicles increased for all three fields, by up to 11% (Figure 5-5).

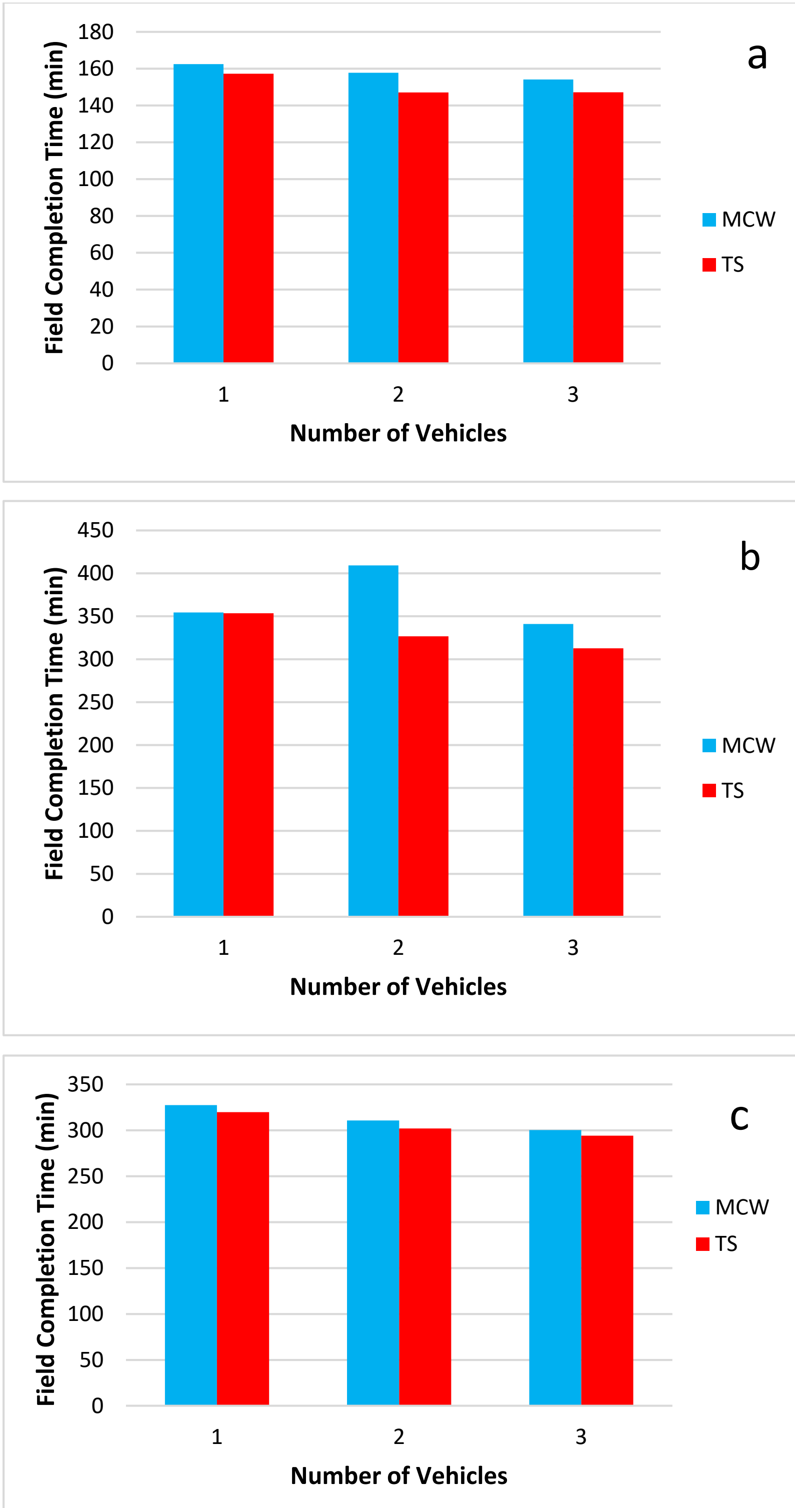


Figure 5-5. Field completion time reduction through replacing a single reference machine with two and three smaller ones, in addition to field completion time while different number of vehicles are working together to conduct the operation in (a) Jutland (b) Russellville (c) Versailles field through computer generated routings of MCW and TS procedures.

Table 5-3. Field completion time improvement when deploying relatively smaller vehicles with routing based on Tabu Search

Field	Field Completion Time				
	1 Machine	2 Machines		3 Machines	
	(min)	(min)	(Improvement from 1 machine)	(min)	(Improvement from 1 machine)
Jutland, Denmark	171	154	9.9%	153	11%
Russellville, Kentucky	353	327	7.4%	313	11%
Versailles, Kentucky	320	302	5.6%	294	8.1%

5.4.3 Field Capacity and Efficiency

5.4.3.1 Effective Field Capacity

The effective field capacity improved as the number of smaller machines replaced with the reference single machine increased (Table 5-4). There was an interesting trend in the improvement of this field work parameter in that the second stage of the downsizing (replacing three smaller machines with the two small machines) increased the parameter by nearly 50% of the first stage (replacing two small machines with the reference single machine), for all the fields. This indicates the magnitude of change rate with respect to the field capacity is predominantly and linearly dependent upon the ratio of downsizing. The results also illustrated the magnitude of change rate was the highest for the Jutland field, by 16%, and the lowest for the Versailles field, by 8.5%. This stems from the number of turns as well as the type of turns that the vehicles take to cover the corresponding field. The Versailles field was already finely divided with the implement widths from the original tractor routes so the improvement from increased size reductions was less.

Table 5-4. Field work parameters while smaller vehicles being utilized

Parameter	**Field**	**1 Machine**	**2 Machines**		**3 Machines**	
		Parameter	**Parameter**	**(Improvement from 1 machine)**	**Parameter**	**(Improvement from 1 machine)**
Effective Field Capacity (ha h^{-1})	Jutland, Denmark	6.29	6.98	11%	7.30	16%
	Russellville, Kentucky	12.1	13.1	8.3%	13.7	13%
	Versailles, Kentucky	2.93	3.10	5.8%	3.18	8.5%
Field Efficiency (%)	Jutland, Denmark	84	90.5	7.7%	90.1	7.3%
	Russellville, Kentucky	85.4	90.1	5.5%	93.4	9.5%
	Versailles, Kentucky	88.9	92.6	4.2%	94.4	6.2%

5.4.3.2 Field Efficiency

As with the field capacity, field efficiency as another parameter of interest consistently improved due to the replacement. Although the field efficiency using the original machine was above 80%, using smaller machines could still improve this parameter more than 9% (Table 5-4). There were larger increases in field efficiency when the starting efficiency was lower. This was not unexpected as the amount of the efficiency increases, the improvements happen at a slower rate. Finally, downsizing the machine did always produce increases in field efficiency. While replacing the single machine with multiple smaller ones did always increase field efficiency, in the Jutland field, the highest field efficiency was obtained with two vehicles rather than three.

For completion time, field efficiency and field capacity, the field in Versailles saw smaller percentage improvements than the other fields. This is likely because the small original implement width in relation to the field area already produced more paths in the field, which enabled the original solution to recognize the benefits of reduced double coverage in the headlands and other similar efficiencies. An interesting area of further research would be to significantly expand this investigation and attempt to determine how much the improvement with multiple vehicles is based on smaller implements and how much is based on more effective routing with multiple vehicles providing increased flexibility.

5.5 CONCLUSIONS

In this work replacing of an individual original machine with a number of smaller machines was studied in terms of the field work parameters. To that end, the field task for a single larger machine was converted into the task of two and three smaller vehicles. Newly re-generated working paths reduced working width to one-half and one-third of the width of the original machine, yet preserved the geographical properties of the fields. New routes were generated using a modified Clarke-Wright algorithm and a Tabu Search algorithm and a fitness function that sought improvements in both field efficiency and effective field capacity (respectively total machine time and field completion time).

In all three fields the time to complete the field work reduced, up to 11%, when a single larger vehicle was replaced by a number of smaller vehicles to carry out the same operation. The reductions varied with respect to the number of engaged vehicles and shape complexity of the fields. It was necessary to use Tabu Search to produce the new routes as the simpler CW algorithm did not always provide improvements. Effective field capacity also saw improvements of up to 16% as a single vehicle was replaced with multiple smaller ones. Additionally, the field efficiency metric improved when replacing a single large vehicle with smaller ones, by up to 9.5%. Finally, improvements from using multiple machines were larger when the field efficiency of the original route was lower.

CHAPTER 6: SUMMARY AND CONCLUSIONS

The primary goal of this dissertation was to provide solutions for logistics in agriculture, as computer scientists, operations management specialists and others researching logistics have long realized the importance of efficient routing of multiple vehicles. The VRP is a valuable tool for optimizing path allocation to finish fields as quickly as possible with multiple vehicles. To that end, the allocation and ordering of field paths among a number of involved machines have been transformed into a solvable Vehicle Routing Problem (VRP). A basic heuristic algorithm (a modified form of the Clarke-Wright algorithm) and a meta-heuristic algorithm, Tabu Search, were employed to solve the VRP. In addition, the parameters of the VRP were changed into a dynamic, multi-depot representation to enable to re-route the vehicle even as the operation is ongoing. Finally, the accuracy of the VRP representation of field works and the ability of this optimization procedure to reduce field work times verified. Experiments were conducted using three tractors during a rotary mowing operation. Furthermore, computer simulations were conducted for various fields with different characteristics to investigate the field work parameters when replace an individual big machine with a number of smaller machines.

6.1 MAJOR CONCLUSIONS

Major findings from this research are summarized as follows:

- The standard field work problem can be transformed into a VRP. This transformation enabled optimization of field work parameters when multiple vehicles are working together, based on criteria important to farmers.
- Tabu Search algorithm as a meta-heuristic procedure and Clark-Wright algorithm as a heuristic procedure always generated feasible solutions for the VRP. Solutions provided by the Tabu Search yielded more optimum results than the exact solutions of the Clark-Wright algorithm.
- Tabu Search yielded better solutions as larger numbers of vehicles are deployed in more complicated fields.
- The dynamic, multi-depot VRP can be used as route updating procedure of multiple vehicles in agriculture fields while the operation is in progress. In all

three common scenarios of 1) re-routing following changes in the number of vehicles, 2) re-routing arising from unexpected behaviors (working speed) of the vehicles, and 3) re-routing due to changes in area coverage, this model was able to produce new optimized routes.

- The magnitude of either loss or improvement of the field work parameters, due to re-routing, changed according to the trigger event.
- The magnitude of the changes in the field work parameters changed based on when the trigger event took place. In general, the procedure was able to provide better outcomes if the change in field conditions occurred at a point in time when less of the field was complete and there was more flexibility in the final routing.
- A field work operation when different number of vehicles are working together can be transformed into a vehicle routing problem effectively.
- A reduction in both time to complete the field and the total operating time of the vehicles through the computer-generated optimized routes was confirmed.
- The computer model accurately predicted field working times of different routings.
- The task of a single large machine in real-world fields can be converted and assigned to a number of smaller machines.
- In investigated examples, this replacement of a large machine with 2 or 3 smaller machines improved the effective field capacity, by 7%, and the field efficiency, by 3.8%.
- Time reduction in field completion time varied with respect to the number of engaged vehicles and complexity of the fields in terms of shape, when replacing an individual large machine with multiple small machines.

CHAPTER 7: FUTURE WORK

Following changes in the parameters of the VRP, the dynamic, multi-depot VRP was shown to be able to reset the paths allocated to each vehicle involved in the operation at the same time when the operation was ongoing. The effective field capacity, as the primary parameter of interest, was maintained within ±5% of the pre-determined solution in half of the rerouting scenarios. An important area of further study would be to identify the factors that make it difficult for the optimization model to produce better routes. As such by mitigating those factors, the procedure would be able to maintain effective field capacity within ±5% for the other half of the scenarios when resetting of the routes is commanded.

The solutions from the Modified Clarke-Wright were calculated so quickly that on modern processers, the solution was generated nearly instantaneously. Tabu Search was much more computationally expensive. The total run time to generate an acceptable solution was highly variable and depended on field complexity, number of vehicles and the initial solution used to seed the Tabu Search. Considering the importance of time for both farmers and machinery owners, further research needs to be conducted on reducing the computation time to near real-time. As such, the procedure would be used in real-world operation.

Computer simulations in this work demonstrated noticeable improvements in the effective field capacity and the field efficiency when an individual big machine is replaced with a number of smaller machines. However, initial cost and annual operating cost, such as labor cost, repairs and maintenance, and fuel consumption, are important factors for machinery managers to consider this replacement paradigm in reality. Hence, further studies are required to investigate the feasibility of this transition by integrating benefits achieved from field work efficiencies and the premiums arisen from this replacement.

Throughout this work, computer simulations revealed various magnitudes of improvements for the field work efficiencies when different numbers of vehicles were working together to complete the operation. A number of important factors such as the number of vehicles, the size of the vehicles, the shape of field, and the size of the field influenced the magnitude of improvements. Therefore, a research needs to be carried out to determine the optimal number of vehicles with the same kinematic properties, such as working width and size. This will provide machinery managers with a tool to easier make decisions and deploy minimum number of vehicles while maintaining the field work efficiencies similar to the optima.

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Senneff, A. M., Leiran, B. G., & Roszhart, T. J. (2012). Method and system for generating end turns: U.S. Patent No. 8,209,075.

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Sachs, J. L., Roszhart, T. J., Schleicher, T., Beck, A. D., & Bezdek, M. A. (2012). System and method for generation of an inner boundary of a work area: U.S. Patent No. 8,204,654.
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Shearer, S. A., Pitla, S. K., & Luck, J. D. (2010a). *Trends in the Automation of Agricultural Field Machinery*. Paper presented at the Club of Bologna, Bologna, Italy.
Shearer, S. A., Pitla, S. K., & Luck, J. D. (2010b). Trends in the Automation of Agricultural Field Machinery. *Biosystems and Agricultural Engineering, University of Kentucky, Lexington, USA, 10*.
Spekken, M., & de Bruin, S. (2013). Optimized routing on agricultural fields by minimizing maneuvering and servicing time. *Precision agriculture, 14*(2), 224-244. doi:10.1007/s11119-012-9290-5
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Tullberg, J. (1990). *Why control field traffic.* Paper presented at the Proceedings of Queensland Department of Primary Industries Soil Compaction Workshop. Toowoomba, Australia.
Vougioukas, S. (2009). *Coordinated master-slave motion control for agricultural robotic vehicles.* Paper presented at the 4 th IFAC International Workshop on Bio-Robotics, Information Technology, and Intelligent Control for Bio-Production Systems. September.
Vougioukas, S. G. (2012). A distributed control framework for motion coordination of teams of autonomous agricultural vehicles. *Biosystems Engineering, 113*(3), 284-297.

VITA

Hasan Seyyedhasani

EDUCATION

- M.S. Mechanical Engineering of Agricultural Machinery,
  University of Tehran, Tehran, Iran, November 2010, Advisor: Ali Jafari, Ph.D.
  Thesis: Design, Development, and Evaluation of Hydrostatic Drive for Traveling Mechanism on John Deere 1165 Combine Harvester. GPA: 3.45
- B.S. Mechanical Engineering of Agricultural Machinery, University of Tehran, Tehran, Iran, July 2006. Concentration: Electronic Control Unit (ECU). GPA: 3.03

PROFESSIONAL POSITIONS

- Graduate Research Assistant, Biosystems and Agricultural Engineering, University of Kentucky (December 2013- Present)
- Project Manager, Research and Development Department, Iran Combine Manufacturing Company [*] (ICM. Co.) (October 2008- November 2013)
- After Sales Services Department, ICM. Co. (November 2006-October 2008)
- Plastic Injection Molding Company (July 2005-January 2006)

FUNDED RESEARCH PROPOSAL

- **Seyyedhasani, H**., Jafari, A. 2009. Design, Development, and Evaluation of Hydrostatic Drive for Traveling Mechanism on JD 1165 Combine Harvester. $6,000, Mine and Industry Ministry, Under contract number: 450/51027041. Role: PI

[*] Affiliated with John Deere Company prior to 1982.

SCHOLASTIC AND PROFESSIONAL HONORS

- Graduate Student Professional Travel Funding, $375 (March 2017), Awarded by the Gamma Sigma Delta, University of Kentucky Chapter.
- Scientific Publication Scholarship Award, $500 (November 2016), Recognized contribution to Biosystems and Agricultural Engineering Department, University of Kentucky
- Research highlig**ht** (April 2015), Handheld Devices Provide Poor Location Accuracy, *Successful Farming*.
- Ranked in the top %1 (August 2008), Among all participants in the National Entrance Exam for M.S.
- Distinguished award of Exemption for Military Service (April 2005), Thanks to achieving second-rank at the Nationwide Entrance Exam of

PROFESSIONAL PUBLICATIONS

- **Seyyedhasani, H**., Dvorak, J.S. 2017. Using the Vehicle Routing Problem to Reduce Field Completion Times with Multiple Machines. Computers and Electronics in Agriculture, 134: 142-150.
- **Seyyedhasani, H**., Dvorak, J.S., Sama, M.P., Stombaugh, T.S. 2016. Mobile Device-Based Location Services Accuracy. Applied Engineering in Agriculture (ASABE), 32(5): 539-547.
- **Seyyedhasani, H**. 2017. Annual Operating Cost for Multiple Machines versus Single Machine. Agricultural Research & Technology: Open Access Journal, 4(4): 555643.
- **Seyyedhasani, H.,** Dvorak, J.S. Reducing Field Work Time Using Fleet Routing Optimization. Biosystems Engineering. "Under Review"
- Sarvandi, M., Najafizadeh, M., **Seyyedhasani, H**., Ehsanifar, M., and Hedayati, H. 2017. Non-Linear Response of Torsional Buckling Piezoelectric Cylindrical Shell Reinforced with DWBNNTs Under Combination of Electro-Thermo-Mechanical Loadings in Elastic Foundation. Chinese Journal of Mechanical Engineering. "In Press"

- **Hassani, H.S**., Jafari, A., Mohtasebi, S.S., and Setayesh, A.M. 2010. Transient Heat Transfer Analysis of Hydraulic System on JD 955 Harvester Combine by Finite Element Method. Journal of Food, Agriculture & Environment, 8(2): 382-385.
- **Hassani, H.S**., Jafari, A., Mohtasebi, S.S., and Setayesh, A.M. 2011. Fatigue Analysis of Hydraulic Pump Gears of JD 1165 Harvester Combine through Finite Element Method. Trends in Applied Science Research, 6(2): 174-181.
- **Hassani, H.S**., Jafari, A., Mohtasebi, S.S., and Setayesh, A.M. 2011. Hydraulic System of JD 955 Combine Harvester as Well as Presented Services Based on Statistical Analysis. Asian Journal of Agricultural Research, 5(1): 67-75.
- **Hassani, H.S**., Jafari, A., Mohtasebi, S.S., and Setayesh, A.M. 2011. Investigation on Grain Losses of the JD 1165 Combine Harvester Equipped with Variable Pulley and Belt for Forward Travel. American Journal of Food Technology, 6(4): 314-321.
- **Hassan, H.S**, Ali, J., Seyed, S., and Ali, M. 2010. Fatigue Analysis of Hydraulic Pump Gears of JD 955 Harvester through Finite Element Method. Journal of American Science, 6(7): 62-67.

PROFESSIONAL PRESENTATIONS

- **Seyyedhasani, H**., Sama, M., Dvorak, J.S. Aerial Validation of a Logistics Model for Area Coverage in Agriculture, ASABE Annual International Meeting, July 16-19th, 2017, Spokane, WA, As Speech. (Upcoming)
- **Seyyedhasani, H**., Dvorak, J.S. Comparison of Traditional Path Assignment for Multiple Vehicles with Computer Generated One in Agricultural Field Context, ASABE Annual International Meeting, July 17-19th, 2016, Orlando, FL, As Speech.
- Dvorak, J.S., **Seyyedhasani, H**. Simple Field Logistics Simulation Comparing Field Efficiencies and Field Capacities between Larger and Smaller Equipment, ASABE Annual International Meeting, July 17-19th, 2016, Orlando, FL.

- **Seyyedhasani, H**., Dvorak, J.S. Multi-Vehicle Path Planning and Coordination in Agricultural Fields, ASABE Annual International Meeting, July 26-29th, 2015, New Orleans, LA, As Speech.
- Javanshir, M**., Seyyedhasani, H**., Anajafi, S. Application of New Technologies in Agricultural Machinery, the 7th National Conference on Agricultural Machinery Engineering & Mechanization, September 5-6th, 2012, Shirza University, Shiraz, Iran.

PROFESSIONAL RESEARCH PROJECTS

Biosystems and Agricultural Engineering Department

- Efficient Routing of Multiple Vehicles for Agricultural Area Coverage Tasks. (2015), Dvorak, J.S., Sama, M.P. $30,000, KSEF-3583-RDE-019. Role: Senior Personnel
- Location services (GPS, Network, Google Services) accuracy of mobile devices. (2014), USDA National Institute of Food and Agriculture (NIFA) Hatch Multistate project under 1001110. Role: Senior Personnel

Iran Combine Manufacturing Company

- Project Manager of Engine of 1055 Combine Harvester (2009-2013)
- Project Manager of Compressed Air Generation System (November 2013)
- Yield Monitoring System (December 2012)
- Project Manager of Brake and Clutch System (June 2012)
- ECU and GPS Systems (December 2011)
- Project Manager of Straw Chopper Machine (July 2011)
- Hydrostatic Drive for Traveling Mechanism (November 2010)
- Vibration Monitoring and Noise Emission (September 2010)
- Managed as Manager of Research and Development Department (March 2013-September 2013)

Private Sector

- Hydrostatic Drive Test for Propulsion (May 2012)

TEACHING EXPERIENCE

- Fluid Power Systems (BAE 515), Biosystems and Agricultural Engineering, University of Kentucky, Spring 2014 and 2015.
- Power Train, Engine, and Hydraulic Systems of JD 955 and 1165 combine harvesters, (2006-2008).
- Electrical, and Hydraulic Systems combine harvester of JD 1450 and SAMPO 3065L (2006-2008).
- Operation and Adjustment for JD 349 and 359 Balers, (2006-2008).
- Operation, adjustments, and service and maintenance of combine harvesters (2006-2008).

EXTENSION ACTIVITIES

Outreach Presentations and Workshops

Location (Province City)	Date	Audience	Topic	Program Period (days)
Qom Qom	February 2007	Farmers, Students, Agricultural Engineers & Experts	Operational* JD 955 Harvester	1
Ardabil Ardabil	March 2007	Farmers	Operational, Technical** JD 955 Harvester	3
North Khorasan Esfarayen	April 2007	Farmers, Students and Agricultural Engineers & Experts	Operational, Technical JD 955 Harvester, Balers	4
Khuzestan Lali	April 2007	Agricultural Engineers & Experts	Operational, Technical JD 1165 Harvesters	3
Esfahan Esfahan	May 2007	Agricultural Engineers & Experts	Operational JD 955, and JD 1165 Harvester	3
Lorestan Azna	May 2007	Farmers, Students and Agricultural Engineers & Experts	Operational JD 955 Harvester	1
Zanjan Zanjan	June 2007	Farmers and Students	Operational, Technical JD 955 Harvester	3

Lorestan Malayer	May 2007	Agricultural Engineers & Experts	Operational Balers	1
Fars Shiraz	June 2007	Agricultural Engineers & Experts	Technical SAMPO 3065L Harvester	2
Hamedan Bahar	August 2007	Farmers, Students and Agricultural Engineers & Experts	Operational JD 955 Harvester	1
ICM. Co	February 2008	JD 1165 Harvester customers in the last year (30 Persons)	Operational, Technical JD 1165 Harvester	4
ICM. Co	February 2008	JD 1165 Harvester customers in the other year (27 Persons)	Operational, Technical JD 1165 Harvester	4
Zanjan Zanjan	March 2008	Farmers and Students	Operational, Technical JD 955 Harvester	3
Ardabil Ardabil	March 2008	Farmers	Operational, Technical JD 955 Harvester	3
Sistan & Baluchestan Zabol	April 2008	Agricultural Engineers & Experts	Operational JD 955 Harvester	1
Sistan & Baluchestan Zahedan	April 2008	Farmers, Students and Agricultural Engineers & Experts	Operational, Technical JD 955 Harvester, and Balers	3
Esfahan Esfahan	April 2008	Farmers, Agricultural Engineers & Experts	Operational JD 955, and JD 1165 Harvester	3
Hamedan Hamedan	May 2008	Agricultural Engineers & Experts	Operational JD 955 Harvester	1
Chaharmahal & Bakhtiyari Shahr-e-Kord	May 2008	Farmers, Students	Operational JD 955 Harvester	2
Ardabil Parsabad	May 2008	Farmers, Students and Agricultural Engineers & Experts	Operational JD 955 Harvester	2
Hamedan Nahavand	June 2008	Farmers, Students and Agricultural Engineers & Experts	Operational JD 955 Harvester	1
Zanjan Zanjan	June 2008	Farmers, Students and Agricultural Engineers	Operational, Technical JD 955 Harvester	3

Fars Marvdasht	July 2008	Farmers	Operational, Technical JD 955 and JD 1165 Harvesters	3
ICM. Co	August 2008	After Sales Services Experts and Technician Serving Farmers	Operational, Technical JD 955 and JD 1165 Harvesters	2

* Denotes operation, adjustments, and service and maintenance training
** Indicates power train, engine, electrical, and hydraulic systems training

Exhibition Presentations

- The 8th international Exhibition of Agricultural Factors, Machinery & Mechanization, February 12-15th, 2013, Mashhad, Iran.
- Agrotech-Agropars, The 7th international Exhibition of Agricultural Machinery, Pesticides, Seeds and Water Supply, May 9-13th, 2011, Shiraz, Iran.
- Agrotech-Agropars, The 6th international Exhibition of Agricultural Machinery, Pesticides, Seeds and Water Supply, May 4-7th, 2010, Shiraz, Iran.
- Annual Exhibition of Agricultural Machinery and Related Industries, April 10-12th, 2008, Arak, Iran.

Individual Outreach

- Each customer of JD 1165 and SAMPO 3065L Combine Harvester

SERVICE

National

- Cloud Computing and Internet of Things in Agriculture Apps Session Reviewer/Moderator– Sponsored by Technical Community of Information, Technology, and Sensor Control Systems (ITSC-254), ASABE Annual International Meeting, 2017, Spokane, WA. (Upcoming)
- Big Data, Data Analysis, and Apps Session Reviewer/Moderator– Sponsored by Technical Community of Information, Technology, and Sensor Control Systems (ITSC-254), ASABE Annual International Meeting, 2016, Orlando, FL.
- ASABE Journals Reviewer, 2017

- 2017 Undergraduate Summer Research and Creativity Grants (SRG), University of Kentucky, 2017
- Science Alert Journals Reviewer, 2017
- ASABE MS-58 Agricultural Equipment Automation, 2015-Present
- ASABE ITSC-254 Emerging Information Systems, 2015-Present
- ASABE ITSC-353 Instrumentation and Controls, 2015-Present

Departmental

- Graduate Recruitment Team 2017
- Departmental Seminar Committee 2015-2016, Student Member
- Graduate Recruitment Weekend 2016
- Graduate Student Blog Team 2016

Corporate

- Fluid Power Team of the ICM. Co. Executive Member, 2007-2013
- Research and Development Representative in European Foundation for Quality Management (EFQM) Audit, 2009-2013
- Research and Development Representative in Technical Meetings with Overseas Suppliers and Customers, 2009-2013

PROFESSIONAL ORGANIZATIONS

- The Unmanned Systems Research Consortium (USRC), University of Kentucky, Student Member
- The American Society of Agricultural and Biological Engineering (ASABE), Member Since 2014
- The International Honor Society of Agriculture, Gamma Sigma Delta, Member
- Iranian Society of Agricultural Machinery Engineering and Mechanization (ISAMEM), Member
- Agricultural and Natural Resources Engineering Organization, Iran (ANREO), Member

PROFESSIONAL DEVELOPMENT

Professional Meetings Attended

- ASABE Agricultural Equipment Technology Conference. Louisville, KY, 2017.
- ASABE Annual International Meeting. Orlando, FL. 2016.
- ASABE Annual International Meeting. New Orleans, LA. 2015.
- ASABE Agricultural Equipment Technology Conference. Louisville, KY, 2015.
- The 8th international Exhibition of Agricultural Factors, Machinery & Mechanization, Mashhad, Iran, 2013.
- Agrotech-Agropars, The 7th international Exhibition of Agricultural Machinery, Pesticides, Seeds and Water Supply. Shiraz, Iran, 2011.
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