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Using the Vehicle Routing Problem to Reduce Field Completion Times with Multiple Machines

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Seyyedhasani, Hasan and Dvorak, Joseph S., "Using the Vehicle Routing Problem to Reduce Field Completion Times with Multiple Machines" (2017). *Biosystems and Agricultural Engineering Faculty Publications*. 71.

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Digital Object Identifier (DOI)

<https://doi.org/10.1016/j.compag.2016.11.010>

Notes/Citation Information

Published in *Computers and Electronics in Agriculture*, v. 134, p. 142-150.

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The document available for download is the authors' post-peer-review final draft of the article.

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9 **Keywords:** Vehicle Routing Problem, Effective Field Capacity, Field Efficiency, Agricultural

10 Machinery, Tabu Search, Simulation

1 ABSTRACT

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.

1 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., 2010). 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 (Bochtis and Vougioukas, 2008; Hameed et al., 2010; Jin and Tang, 2010; Oksanen and Visala, 2009; Palmer et al., 2003; Spekken and de Bruin, 2013). Although larger and faster machines significantly improve capacity, they also cause compaction (Blackmore et al., 2002; Hamza and Anderson, 2005). Researchers have even explored routing optimization for vehicles to specifically reduce compaction potential (Bochtis et al., 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 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 et al. (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 et al., 2006) and three dimensional environment modelling (Emmi et al., 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 and 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 in designated locations (Toth and 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 and Vigo, 2002) to agricultural field applications (Bochtis and Sørensen, 2009; Conesa-Muñoz et al., 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. 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 and 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 and Wright, 1964). This algorithm produces reasonable solutions quickly (Toth and 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 (Bochtis et al., 2013; Spekken and 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 et al., 2009). Unfortunately, the most popular metaheuristics, such as neural networks or genetic algorithms, are not efficient at exploring the solution space posed by the VRP (Toth and Vigo, 2002). Nevertheless, researchers have successfully applied modified versions of genetic algorithms for routing of vehicles in agricultural fields (Alba and Dorronsoro, 2004; Hameed et al., 2011) and controlling robots in greenhouses (Komasilovs et al., 2013). However, for VRP, Tabu Search has been identified as much more efficient at identifying solutions to the VRP (Toth and 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 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 1. Steps in the field path allocation and route creation process.

2.1 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 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 2b).

Figure 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 2cError! Reference source not found.), 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 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 $\{i_2, \dots, i_{|R_j|-1}\} \subseteq N \setminus \{0\}$, and

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

There are alternative notations for expressing the VRP (Toth and Vigo, 2002), but for consistency with publications in agricultural machinery we have adopted Bochtis and Sørensen (2009) notation. 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)

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

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:

(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 (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:

(3)

$$\min \left(z \text{ cost}_{last} + (1 - z) \frac{\text{cost}_{all}}{|V|} \right), z | 0 \leq z \leq 1$$

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.

2.2 VRP SOLUTION METHODS

2.2.1 Modified Clarke-Wright

The Clarke-Wright Savings Algorithm (Clarke and 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 and 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 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 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 4).

Figure 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.

2.2.2 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.

2.3 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 5). The total path length was 13,200 m with the longest path at 930 m.

Figure 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 6). The paths in this field were provided as an example of optimal path direction in the path creation research by 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 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.

3 RESULTS

3.1 VRP TRANSFORMATION

The VRP transformation of the test fields resulted in the node placements as shown in Figure 7a for the basic field and 7b for the non-convex field.

Figure 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 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.

329 *Table 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

330
 331 The high number of infeasible arcs complicated the solution space and limited solution methods as
 332 those that attempt random selections would mostly select infeasible arcs. However, the normal
 333 constraints within the VRP already make it difficult to solve with such methods so this limitation was
 334 not too severe. More importantly, this VRP transformation did create a representation that enabled
 335 assigning travel times to every path in the field while still ensuring all fieldwork paths are traversed.

336 **3.2 SOLUTION METHODS**

337 Both the Modified Clarke-Wright Savings Algorithm and Tabu Search always generated solutions
 338 containing only feasible arcs and included all required arcs. Figure 8 shows a representative example
 339 of the solutions generated by each of these techniques. The displayed solutions are for the non-
 340 convex field with five vehicles. As expected, the Modified Clarke-Wright method assigned paths to
 341 each vehicle that are closely grouped to each other since its solution is obtained by dividing a single
 342 long chain of paths. This resulted in three vehicles (represented by purple, blue and yellow) that had
 343 to travel to the far end of the field to start or finish working. The Modified Clarke-Wright method
 344 produced a solution not unlike that used by many producers today, where one vehicle sets an A-B
 345 line and provides the coordinates to the other vehicles. The drivers then try to divide the field evenly
 346 and drive to their sections, which they will work until they meet the work performed by the other
 347 drivers. The Tabu Search eliminated more of the inefficient non-working travel time and utilized the
 348 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 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 processors, 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.

3.3 FIELD COMPLETION TIMES

3.3.1 Basic Rectangular Field

As Figure 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 9. Comparison of time until field completion 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 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 10. Effective field capacity (both total and per vehicle) in the basic field.

3.3.2 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 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 8 with 5 vehicles, but the difference in completion times between the solutions shown in Figure 8a and Figure 8b is 21% (the 5 vehicle point in Figure 11).

Figure 11. Comparison of time until field completion 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 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 12. Effective field capacity in the non-convex field.

4 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 et al., 2010; Shearer et al., 2010). 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 and 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.

5 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 Clarke-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.

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