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Using the Vehicle Routing Problem to reduce field completion times with multiple machines

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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.

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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

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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 meta-heuristics, 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 (see Fig. 1).

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