MODELING AND ANALYSIS OF GROUND-BASED AUTONOMOUS AGRICULTURAL VEHICLES

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To my loving wife Leah and my amazing girls, Hannah and Millie, for putting up with me and supporting me when I decided that my previous seven years of college just weren't long enough.

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ABSTRACT

Wilfong, Gabriel J. Ph.D., Purdue University, August 2019. Modeling and Analysis of Ground-based Autonomous Agricultural Vehicles. Major Professor: John Lumkes.

In the years to come, a growing global population will require more crop production than ever before. As technological advances improve across all industries, autonomous agricultural vehicles (AAVs) can be part of the solution to the rising demand for food. By improving and transforming conventional farming methods, AAVs have the potential to transform the way farming operations are completed. AAVs are a class of robotic machines that have the ability to complete agricultural tasks without requiring direct and constant control of a human operator. By removing the need for an operator, these agricultural robotic machines allow for new vehicle designs and new opportunities for different vehicle configurations and sizes.

A simulation model was developed that calculates the energy requirements of AAVs operating on row crops. This deterministic model was used to quantify the energy needs and energy expenditures of agricultural vehicles, and to investigate the effects of using AAVs in lieu of conventional human-operated agricultural machinery.

The energy model was demonstrated using a pre-defined scenario of a typical row-crop farming operation in the Midwest U.S. The purpose of the case study was to compare a conventional crop production operation with operations that have implemented autonomous machines. Four general vehicle configurations were chosen based on the traction machine size: large tractors (e.g., greater than 60 kW), small tractors (e.g., less than 60 kW), utility vehicles (e.g., John Deere Gator), and single row machines. The complete crop production operation was based on a farm size of 607 ha (1,500 acre) with half the land devoted to corn production. The four main operations were fertilizer application, pesticide spraying, no-till planting, and harvesting.

First, the energy model was used to compare a whole farm operation with three different machine configurations: using all conventional large machines, using all autonomous large machines, and using all autonomous smaller machines (≈55 kW tractor). The results show that from an energy standpoint, the most significant savings comes from the decreased amount of agrochemical application associated with AAVs. The total energy consumption of the large tractor AAV configuration is 36% less than the conventional operation (11,081 MJ/ha vs. 7,090 MJ/ha).

In order to have a better perspective on the effects of using AAVs, further analysis was conducted on an individual operation basis: fertilizing, pesticide spraying, no-till planting, and harvesting. Because AAVs can work 24-hours per day, the fertilizing operation for the single large tractor AAV could be completed in 1.6 working days, as opposed 2.4 working days for the conventional machine. It only required two small tractor AAVs to meet or exceed the performance of the conventional machine, yet for the same amount of money, four to five small tractor AAVs could be purchased.

The greatest benefit to utilizing AAVs is the intelligent application of pesticide, which can allow for 65–95% reduction in chemical use. The spraying operation highlighted the advantages of large machines (conventional and autonomous), namely speed of operation and width. It takes two small tractor AAVs, seven utility AAVs, or 12 single-row AAVs to match their performance.

For the no-till planting operation, two small tractor AAVs, seven utility AAVs, or 39 single-row AAVs are required to match the performance of conventional machinery. However, for the same cost as the conventional machine, six small tractor AAVs, 16 utility AAVs, or 55 single-row AAVs could be purchased. The benefit of using higher numbers of AAVs is seen in the amount of time required to complete the planting task, where the swarms of AAVs could finish planting in nearly 1/4 of the time.

Harvesting was previously analyzed during the whole farm scenario. In general, the energy consumption and costs are relatively the same between the conventional machine and the large AAV. The advantage of the autonomous harvesting is that is can operate continuously throughout the night. Continuous operation is possible for this scenario because corn can be harvested at night. However, soybeans cannot because the onset of dew at dusk does not allow for proper processing of the crop.

Along with the energy model, crop production efficiency metrics were studied that provided an objective method of analyzing the advantages and disadvantages associated with replacing and/or augmenting conventional farming vehicles with AAVs. Energy-per-unit-area shows the amount of energy that is consumed over the entire field, regardless of the task time required. Because labor energy consumption is insignificant compared to the other three inputs, energy-per-unit-area is also independent of the number of machines simultaneously in use. Working days and machinery capital cost are other metrics that proved beneficial when comparing AAVs to conventional machines.

Finally, a modeling tool was developed and demonstrated that allows a user to interact with the energy model in an intuitive way. Creating the modeling tool in Microsoft Excel allows for easy distribution to a wide audience, as opposed to using a more expensive software package. The energy model workbook is composed of five spreadsheets that contain instructions, inputs, outputs, and supporting data tables. A GUI was created using Microsoft Excel VBA that lets the user interact with an event-driven program. Data sets can easily be created and modified for the purpose of evaluating different farming operations. Additionally, options within the GUI allow for parameter studies where multiple data sets can be instantly created in order to analyze the effects of changing a single variable.

1. INTRODUCTION

In the years to come, a growing global population and an increase in biofuel consumption will require more crop production than ever before. By the year 2050, it is estimated that the global population will reach over 9 billion people and will require approximately double the amount of rice, wheat, maize, and soybean compared to 2013 (Ray et al., 2013; Godfray et al., 2010). One approach to this problem is increasing the amount of land used for food production. However, studies have shown that increasing crop yields is a more sustainable way towards meeting future needs and ensuring global food security.

As technological advances improve across all industries, autonomous agricultural vehicles (AAVs) can be part of the solution to this crop production problem. By improving and transforming conventional farming methods, AAVs have the potential to greatly increase crop yields while also decreasing the overall environmental impact of farming. AAVs are an emerging class of robotic machines that have the ability to complete agricultural tasks without requiring the direct and constant control of a human operator. By removing the need for a human operator, these agricultural robotic machines allow for new vehicle designs and new opportunities for different vehicle configurations and sizes. In the future, AAVs will be used for various tasks such as intelligent weeding, targeted microspraying of fertilizer and pesticide, irrigation, planting, harvesting, and transportation.

This research investigates the effects of agricultural robots on the production efficiency of farming operations and proposes different robotic vehicle architectures that will lead to increased crop yields, increased production efficiency, and reduced environmental impact of farming. While machines are used for many different functions and tasks on a typical crop farm, the scope of research has been narrowed to focus on ground vehicles that operate primarily on row crops.

By modeling the functions and tasks of a robotic vehicle, along with crop behavior, the production efficiency can be calculated and compared to conventional farming vehicle techniques. Examples of efficiency metrics could include crop yield per human capital or volume of irrigation water per field area. The purpose of calculating various production efficiencies is to give a better overall picture of the advantages or disadvantages associated with replacing and/or augmenting conventional farming vehicles with AAVs. Once various models are formed, numerous parameters can be changed in order to find optimized configurations and designs of robotic agricultural machines.

Ultimately, there is a growing need for increasing global food production to provide for future generations. This work will assist in identifying key areas of vehicle improvement and new farming methods that will result in increased crop yields, increased production efficiency, and a reduction of the overall environmental impact of farming.

1.1 Research Objectives

This research has three primary objectives. The first objective is to develop a simulation model of AAV energy requirements. This model will follow standard methods of predicting and quantifying energy needs of agricultural vehicles, specifically ground vehicles that operate primarily on row crops. A full energy balance will not be analyzed. Rather, the model will focus on the various inputs necessary for autonomous and conventional agricultural vehicles to complete desired tasks. By quantifying these energy requirements, a greater understanding of the design and capabilities of AAVs will be known.

The second objective is to create crop production efficiency metrics to be used when comparing conventional agricultural machines with AAVs. These efficiency metrics provide an objective method of analyzing the advantages or disadvantages associated with replacing and/or augmenting conventional farming vehicles with AAVs.

Finally, the third objective of this research is to develop and demonstrate a modeling tool that allows users to employ new and efficient methods of using AAVs in the crop production process. By leveraging the energy model and efficiency metrics, parameter studies and what-if analysis will be performed in order to highlight the best use conditions for employing AAVs on farming processes.

1.2 Motivation

Global food security and global food production are issues that affect everyone. As the global population ever increases, measures must be taken now in order to ensure sufficient food production and crop availability in the decades to come. Multiple studies have shown the impending shortfall of food supply if current processes and methods are unchanged. In addition to the need to increase food production, the environmental impact of farming must be minimized. Energy usage, chemical applications, and tillage lead to increased carbon emissions, harmful runoff, and erosion. Finally, fewer agricultural workers are available and labor shortages will continue to become more prevalent in the future to come. One critical way of addressing these future needs is to research the effectiveness of autonomous agricultural vehicles (AAVs). This advanced technology will allow for gains in efficiency and effectiveness of farming operations and help prepare crop production for future demands. This project is significant because it will quantify the requirements of these new robotic farming machines, create metrics to compare conventional agricultural vehicles with AAVs, and introduce unique methods of using AAVs in the crop production process. This research will build the foundation for AAV design and allow for AAVs to be a major player in the effort to provide food for future generations while taking care of the environment.

1.2.1 Growing global demand for crop production

As the world population continues to grow, solutions to increased crop production demands are necessary. It is estimated that the global population will reach over 9 billion people by 2050 (United Nations DESA, 2017). Along with increased global population, overall socioeconomic level is expected to rise as well. These factors are leading to an increased demand for more food and for higher quality food.

In the past 50 years, global population has grown from about 3.3 billion to 7.4 billion (Figure 1.1). Yet, global crop production has been able to keep pace and even exceed population growth; in large part due to advanced farming practices and technologies along with an increased amount of arable land. With the world population more than doubling in the last 50 years, total world crop production has increased by 145% in that same time. This has resulted in an additional 25% more food per person compared to 1960 (Pretty, 2008).

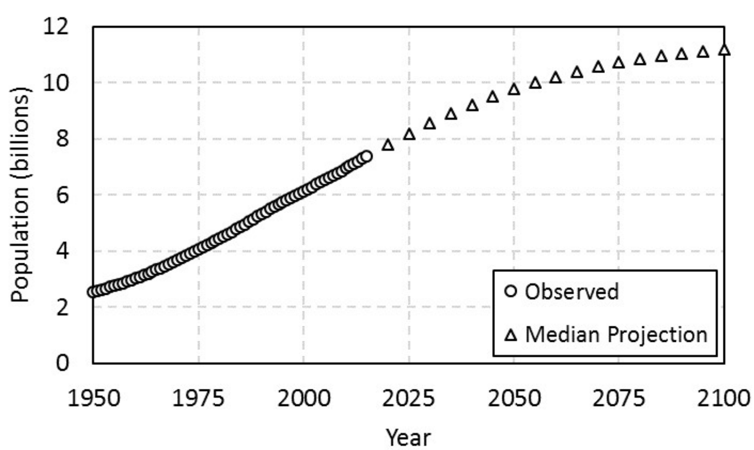


Figure 1.1. Total global population (United Nations DESA, 2017)

Despite this progress in the recent past, indicators are showing that the current growth rate of crop production will not be able to keep pace with demands. Even though the future population growth rate is decreasing, the growth rate for the demand of crop production is continuing to be strong. In addition to increased population, crop production demands are being spurred on through increased demand in meat and dairy consumption (Tilman et al., 2011). As the world slowly becomes more prosperous and individual wealth increases, dietary demands begin to shift towards meat, dairy, and more processed foods (Keyzer et al., 2005). This in turn increases the demand of crops because livestock are primarily raised with inexpensive cereals in industrialized countries (Pretty, 2008).

Additional crop demand also comes in the form of global biofuel consumption. The production and use of biofuels began to quickly expand in the early 2000s (Araújo et al., 2017; Alexandratos et al., 2012). Factors that contributed to this rapid growth include initial government efforts and mandates to reduce greenhouse gas emissions, along with improved energy security. Recent policy decisions have relaxed initial targets, thus the growth rate of consumption has slowed considerably in recent years (OECD, 2016). Yet, the demand for biofuels will continue to be present and exhibit modest growth in the years to come (Figure 1.2).

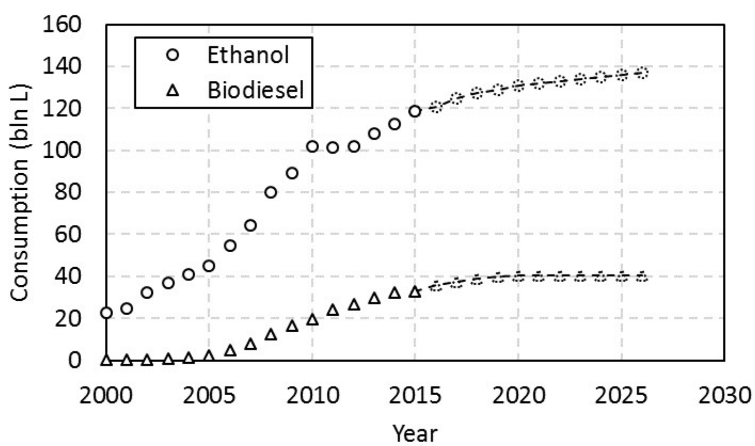


Figure 1.2. Global biofuel consumption (OECD, 2016)

It is projected that global food demand in 2050 will require approximately double the amount of rice, wheat, maize, and soybean compared to 2013. In order to meet this target, a yield rate growth of ~2.4% per year (non-compounding) is required. Current global trends in yield rate growth for rice, wheat, maize, and soybean are 1.0%, 0.9%, 1.6%, and 1.3% per year (non-compounding), respectively. At these rates, global crop production would fall below the necessary levels to meet the projected demands. One approach to closing this yield gap is to increase the amount of land used for crop production. However, studies have shown that increasing crop yields is a more sustainable way towards meeting future needs and ensuring global food security (Ray et al., 2013; Godfray et al., 2010).

1.2.2 Labor Shortage

As demand for crops and food continues to increase, indicators are revealing a growing farm labor shortage. As countries become more wealthy and per-capita income increases, people shift from agricultural to non-agricultural jobs. For example, Figure 1.3 shows the shift in farm labor from 1990 to 2010 for China, Mexico, and the United States. This trend is seen in nearly every other country in the world (Taylor et al., 2012). Governmental immigration policy is also part of the equation. The estimated number of undocumented Mexican immigrants in the United States has fallen by almost 13% since its peak in 2007 and roughly 46% of hired crop farm workers come from this group (Hertz and Zahniser, 2012). Another example is the labor shortages seen in the United Kingdom (UK) after they voted to leave the European Union (EU) and made it harder to obtain immigration worker status. The farming industry in the UK is heavily dependent on labors from elsewhere in the EU. Recent consequences of labor shortages have come in the form of wasted crops because there was not enough workers to harvest everything (Agerholm, 2018). With fewer workers available, AAVs can reduce the need for laborers through mechanizing and automating agricultural processes that are traditionally done by hand (Bonadies et al., 2016).

1.2.3 Environmental Impact of Agriculture

As noted above, increased demands for crop production are beginning to highlight a yield gap between the supply and demand of global food supplies. Yet the question

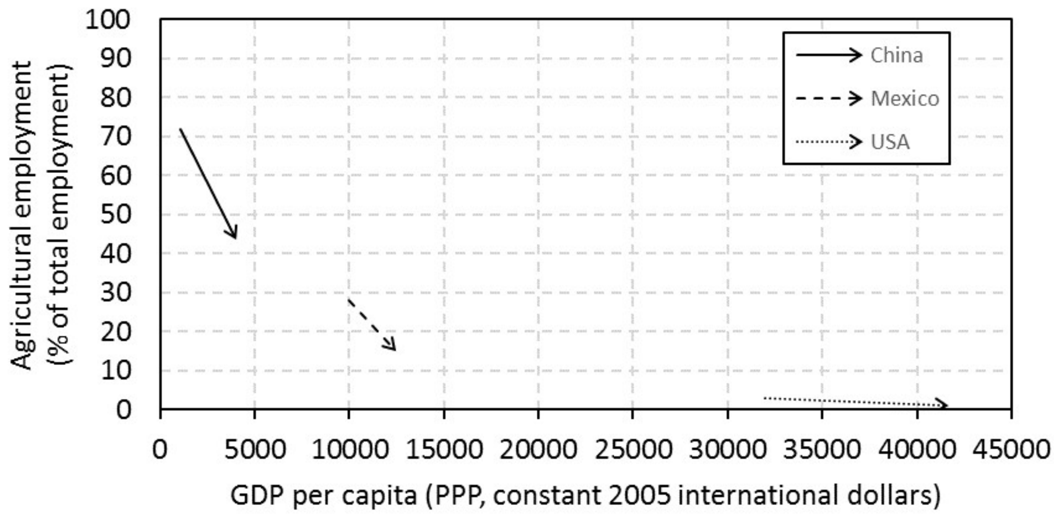


Figure 1.3. Farm labor shift from 1990 to 2010 (Taylor et al., 2012)

remains as how to approach this supply-demand shortfall in a way that meets our needs while protecting the environment. Agricultural practices can be a significant source of harm to the environment, as discussed below.

1.2.3.1 Land Use

With the expansion of crop production since the 1960s, the total land area for agricultural use has increased by 11% and now accounts for approximately 40% of the world's dry land (Ramankutty et al., 2008). This growth has begun to slow in recent decades, yet loss of natural habits and biodiversity still occurs (Ramankutty et al., 2018). Additionally, converting forests, grasslands, and savannahs into agricultural land disrupts water and nutrient cycles and releases carbon dioxide into the atmosphere. It is difficult to pinpoint exact numerical values for the upper limit of suitable global land use for agricultural purposes due to the complex environmental and ecological interactions worldwide. However, a generalized threshold for appropriate global land use can be found by looking at how much more land conversion can occur before permanent environmental damages are no longer acceptable. Research suggests that the expansion of agricultural land (i.e., pastures and cropland) should stabilize by 2020 in order to prevent further biodiversity loss (Van Vuuren and Faber, 2009). If current expansion and practices are not curbed, cropland expansion would surpass this target well before 2050 (UNEP, 2014). Increasing yields while maintaining current levels of agricultural land use is a sustainable way forward in order to meet global food demand while also protecting our environment (Ramankutty et al., 2018).

1.2.3.2 Feed, Weed, and Irrigate

A major factor attributing to crop production more than doubling in the past five decades is the advancement and use of synthetic fertilizers, specifically nitrogen fertilizers. As crop production has escalated, overall fertilizer use has increased over sixfold; with nitrogen based fertilizer usage increasing over ninefold (Figure 1.4).

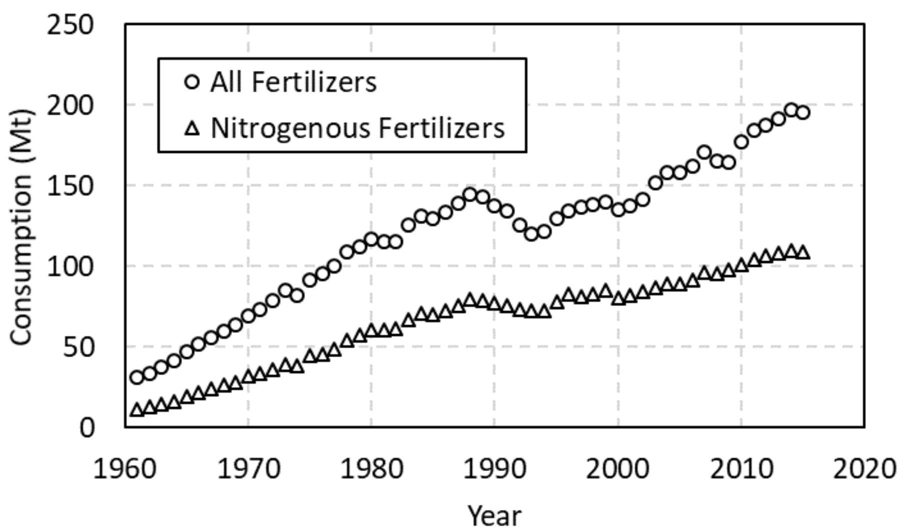


Figure 1.4. Global agricultural fertilizer consumption (FAO, 2017; Pretty, 2008)

There is a clear relationship between increased fertilizer use and increased crop production (Pretty, 2008). This has been beneficial in meeting the demands of global crop production yet also shows a high dependence on their use. For example, 40–60%

of crop yield in the United States and England can be attributed to fertilizer use (Stewart et al., 2005). While fertilizer use has helped feed billions of people world-wide, excessive use and over application can cause harmful effects on biodiversity, soil health, and water quality.

Pesticide use follows a similar trend to that of fertilizers. In the past 25 years, pesticide use and sale has nearly tripled worldwide (Figure 1.5); with 45% used in Europe and 25% used in the United States (De et al., 2014). While pesticides have helped boost productivity and crop yield, they have also had harmful effects on nontarget plants and insects (Ramankutty et al., 2018).

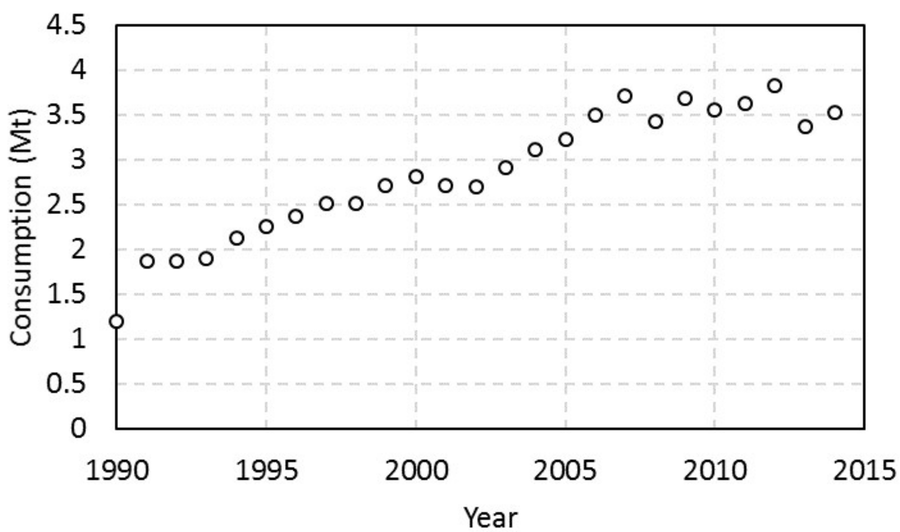


Figure 1.5. Global pesticide consumption (FAO, 2017)

Total land area under irrigation has also doubled since the 1960s (Figure 1.6). Over two-thirds of this area is found in China, India, Pakistan and the United States; with India accounting for half of that area. Agricultural irrigation is responsible for ~70% of global water withdrawals (Gleick et al., 2014). While the use and application of irrigation has boosted crop productivity, especially in precipitation-limited areas, much of irrigation water is used inefficiently. This excess usage can lead to over-saturation of soils, erosion, and salinization (Pretty, 2008). Additionally, water used for irrigation can negatively effect environmental water quality by transporting pesticides, excess nutrients, and livestock antibiotics into local ecosystems. There are also instances of nitrogen and phosphorus fertilizer pollution causing algal blooms and dead zones in freshwater and coastal marine systems (Ramankutty et al., 2018).

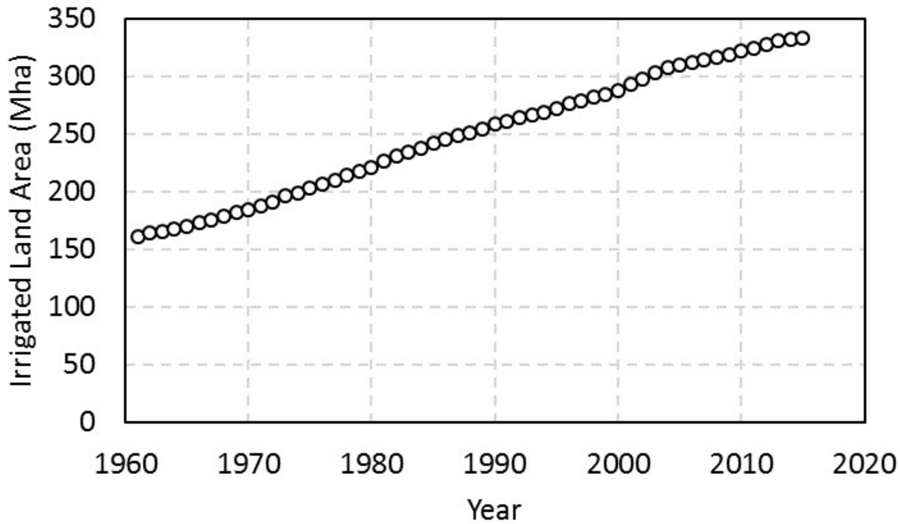


Figure 1.6. Global irrigated land area (FAO, 2017)

1.2.3.3 Fossil Fuel Usage

Increased productivity of cropland has also been driven by advances and increased use of the mechanization of agriculture. The number of agricultural machines has doubled since 1960 (Pretty, 2008). Benefits of agricultural mechanization include: expanded cultivation area, timeliness of field operations for maximum production potential, and the multi-functional capability of machines for use in all areas of agricultural production (Mrema et al., 2015). While increased use of agricultural machines has led to increased yield and greater crop production, it has also greatly increased the amount of fossil fuels consumed (Figure 1.7). This in turn contributes to additional greenhouse gas emissions as a result of fuel combustion.

Another major source of fossil fuel consumption in agriculture is due to the production of fertilizer. The Haber-Bosch process was a major breakthrough in the

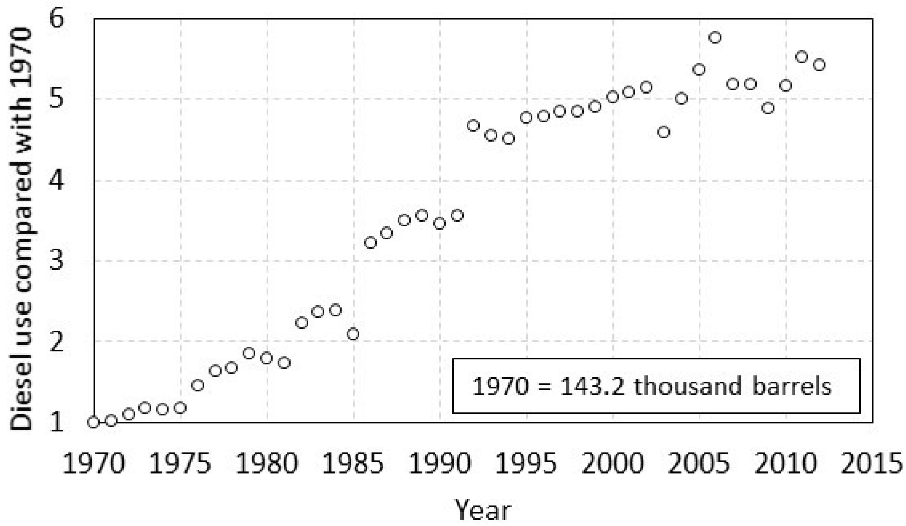


Figure 1.7. Global agricultural diesel use (FAO, 2017)

development of synthetic fertilizers. Through the combination of nitrogen and hydrogen, ammonia is formed; which is a key ingredient to the majority of nitrogenous fertilizers. Nitrogen is readily available in the atmosphere, whereas the key source of hydrogen is natural gas (Gellings and Parmenter, 2009). As mentioned above and shown in Figure 1.4, the use of nitrogen-based fertilizers has been rapidly growing. Because of this increased use and demand, the production of fertilizers consumes ~3% of the world's natural gas production and accounts for ~1–3% of the world's carbon emissions (Zhang, 2016; Bellarby et al., 2008).

1.2.4 Sustainable Intensification

With the need for increased global crop production, and the clear environmental effects of agricultural operations, more sustainable practices must be adopted. Simply decreasing input use (e.g., fuel, water, fertilizers, pesticides) wrongly assumes that this will lead to greater sustainability. In actuality, this short-sided approach can result in agricultural systems that require more land in order to produce the same amount of food output. Sustainable intensification is an alternate approach that aims at increasing yields and food supplies while minimizing or eliminating damage to the environment (Pretty, 2008).

As this term has grown in popularity and use in policy discussions, a unified definition and description still remains somewhat unclear (Rockström et al., 2017; Petersen and Snapp, 2015). However, a general definition and description of sustainable intensification is increasing agricultural output to meet the increasing societal crop production demands while decreasing inputs and protecting and eliminating harm to the environment. Sustainable intensification can be achieved through the combined use of careful ecological practices, state-of-the-art inputs, and innovative technologies (Petersen and Snapp, 2015; Rockström et al., 2017; Friedrich and Kassam, 2016).

AAVs are poised to make a difference in agricultural and crop production practices. By combining cutting-edge methods for navigation, guidance, decision making, and operation, AAVs can bring about new vehicle design and implementation for the purpose of increasing crop yields, increasing production efficiency, and reducing the harmful environmental impacts of farming.

1.3 Primary Contributions

The primary contributions that will result from this research are listed below:

- Quantify energy costs of autonomous agricultural ground vehicles to provide understanding of necessary power requirements
- Develop and compare crop farming production efficiency metrics between conventional and autonomous agricultural vehicles
- Develop and demonstrate a modeling tool that allows users to employ novel methods of effectively and efficiently using AAVs to augment and/or replace conventional farming vehicles

2. BACKGROUND

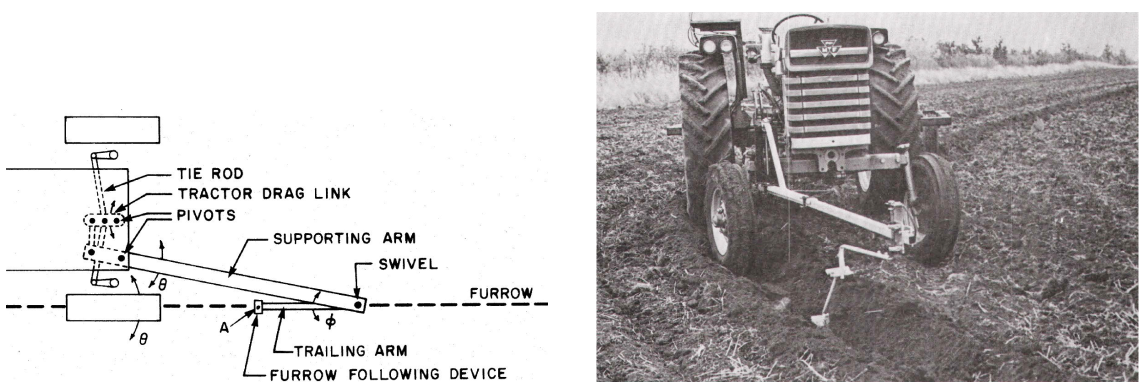
2.1 Autonomous Agricultural Vehicles

Autonomous agricultural vehicles (AAVs) are a class of machines that are able to operate automatically without the need for human intervention. These machines must not only be able to automatically steer or navigate, but also perform purposeful, long-term tasks while being left unattended in real-world environments (Blackmore and Griepentrog, 2006). The general function of AAVs starts with the assignment of a given task, such as precision spraying, crop scouting, or soil sampling. Next, their behavior or control algorithm determines the methods and actions used to complete the given task. A key characteristic of AAVs is their ability to react to external and unforeseen disturbances in intelligent ways so as to maintain focus on task completion while simultaneously preventing damage or harm to their surroundings.

While the scope of this research focuses on ground-based AAVs operating primarily on row crops, it is worth mentioning the ongoing research into autonomous agricultural aircraft. In recent years, the use of small unmanned aerial vehicles (UAVs) for agricultural applications has increased in popularity. These devices have given rise to site-specific farming by using remote sensing to identify variations of crop and soil conditions (Zhang and Kovacs, 2012). Early UAVs were either fixed-wing aircraft or helicopters (Xiang and Tian, 2006; Schmale et al., 2008). Recently, quad- and hexacopters have grown in popularity (Freeman and Freeland, 2015). Commonly referred to as drones, these machines are battery powered, perform vertical takeoff and landing, can precisely hover (even in the presence of strong winds), maneuver at speeds of 50-65 kph, and climb to heights of 1000s of meters (DJI, 2018). The primary limitations to quad- and hexacopters are their limited flight time (i.e., battery capacity) and limited payload capacity (up to 500 g for consumer quadcopter, 6 kg for professional hexacopter). Yet, even with these limitations, UAVs (especially quad- and hexacopters) are actively being used in autonomous applications. For example, Alsalam et al. (2017) developed a quadcopter that traverses a field, identifies weeds, applies herbicide, and collects high resolution images.

2.2 Guidance Techniques of Ground Vehicles

Research into ground-based autonomous agricultural vehicles has been occurring since the 1950s and 60s (Hague et al., 2000). This early work focused specifically on automatic guidance and control of agricultural vehicles and was spurred on by the advancements in control theory in the 1930s, 40s, and 50s. Initial research and effort was directed towards vehicle guidance based on existing features that were formed on a previous pass or operation (Wilson, 2000). Examples of these methods include a mechanical steering linkage that used a furrow following device (Kirk, 1974), as seen in Figure 2.1. This method produced stable results with maximum straight line front wheel tracking error of 3.5 in while operating at a speed of 5.0 mph. Yet its usefulness and stability was limited at higher speeds and required slower speeds while turning (e.g., 2.5 mph for a turning radius of 15 ft).



(a) Furrow following arrangement

(b) Tractor following a curve

Figure 2.1. Mechanical furrow-follower (Kirk, 1974)

Spring-loaded mechanical fingers were used by Swetnam et al. (1981) to detect tobacco plant stalks and greatly decreased effort required to harvest tobacco. Another example of mechanical fingers is the work by Busse et al. (1977), where they were used for detecting stalks on a corn harvester head. Harries and Ambler (1981) used optical electronic sensors as a contactless furrow-following sensor (Figure 2.2). By shining light on a pre-formed furrow, an optical sensor provided steering feedback to a tractor as it traversed a field. This method proved successful in a wide range of conditions, yet failed to produce reliable results when resuming work in the opposite direction after completing a headland turn.

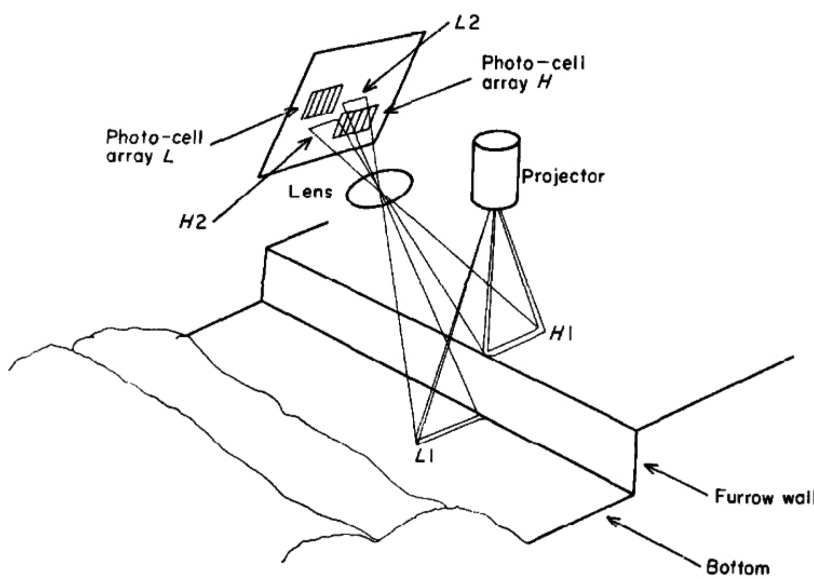


Figure 2.2. Setup of optical furrow-following sensor (Harries and Ambler, 1981)

Another common type of control system that was being explored at the time was guidance with respect to user-generated fixed points in a field (Wilson, 2000). Widden and Blair (1972) proposed a system with a buried cord just below the surface. The cord was drawn up out of the ground and provided guidance and direction for a tractor. It was then re-buried at an offset to provide guidance for the next pass. Leader cables were also proposed for use in agriculture. These permanently installed cables carry a low frequency signal and sensors are used to detect its associated magnetic field for guidance (Tillett, 1991). Radio beacons and systems were also used for fixed-point guidance. For example, Searcy et al. (1990) implemented microwave distance measurements for field location. However, accuracy was somewhat low (±1 m) and the system capability was limited to line-of-site. Other examples of early vehicle guidance techniques include the use of lasers, infrared ranging, rudimentary image analysis, ultrasonics, and dead reckoning (Tillett, 1991).

This early work mainly focused on guidance and steering of agricultural vehicles and had limited applications due to lack of accuracy, lack of range, or being confined to preprogrammed routes. While these methods can still be effective in some modern-day applications (e.g., Pomeroy et al. (2014) successfully demonstrated the benefits of a furrow-following machine for manually-intensive vegetable production), they are unable to react to external environmental disturbances or perform obstacle avoidance.

After the advancements in control theory, the next major breakthrough that allowed vehicle guidance and vehicle autonomy to progress forward was the widespread availability and use of the global positioning system (GPS). GPS allowed for the location of a vehicle to be determined without the need for cables, optical sensors, radio beacons, or mechanical followers. GPS is a satellite-based positioning system that was made available for civilian use in the 1980s, with agricultural research and use accelerating in the 1990s (Stafford, 2000). By using four or more satellites, a GPS receiver collects signals and coverts location data in order to determine a position (Heraud and Lange, 2009). The advent of GPS was very promising, yet it initially suffered from two main limitations: consistent positional accuracy and signal processing delay time due to hardware limitations (Wilson, 2000).

Typical GPS accuracy can be divided up into three categories, as seen in Table 2.1, largely based on the cost of the GPS hardware. In addition to varying device capability, consistent positional accuracy can be affected by terrain and nearby obstacles (e.g., tall buildings or rolling hills), atmospheric conditions, satellite configuration, electromagnetic noise, or software filtering and smoothing (Heraud and Lange, 2009). As technology progressed, new methods were developed to increase positional accuracy and decrease sources of error.

Table 2.1.
Typical GPS Accuracy (Heraud and Lange, 2009)

Type	**Accuracy**
WAAS Enabled	3 m or less
Differential (DGPS)	1 m or less
Real-Time Kinematic (RTK-GPS)	3 cm or less

To achieve the high positional accuracy required for autonomous vehicle navigation, most GPS receivers use differential correction. Differential GPS (DGPS) utilizes an immobile base station in conjunction with four or more GPS satellites. The base station is able to calculate an error with respect to its own GPS-indicated location and transmit that error information to the mobile GPS receiver (Stombaugh, 2018). The most accurate method of DGPS is called Real Time Kinematic (RTK) GPS. With general DGPS use, the corrective base station is not necessarily close to the GPS receiver. RTK GPS utilizes a base station that is usually within 10 km and allows for much greater accuracy than typical DGPS techniques (Heraud and Lange, 2009).

While GPS positional accuracy continues to improve, it is only useful in certain agricultural applications and tasks and is generally necessary but insufficient for true autonomous vehicle operation. GPS guidance and positional information is effective for operations that use path planning where travel routes have been specified. This would include farm-to-field or field-to-field vehicle travel where a navigational software calculates routes based on the desired destination. Another example is the various planned paths for machines as they traverse a field (Figure 2.3). Large-scale operations such as tillage, planting, cultivation, spraying, and harvesting can use path planning for automatic travel through a field. Yet, the level of precision afforded by GPS is not enough for other aspects of autonomous vehicle operation, such as obstacle avoidance or feature recognition.

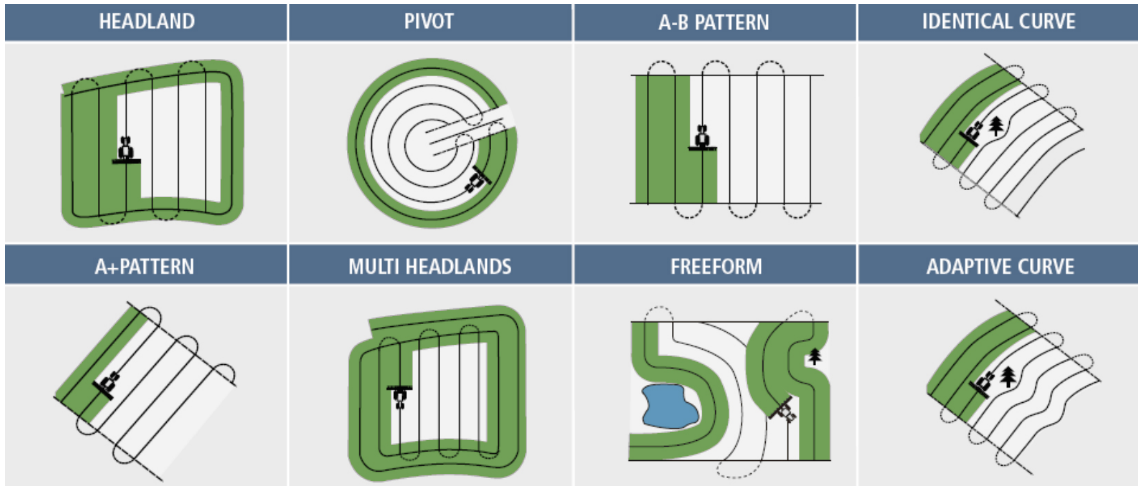
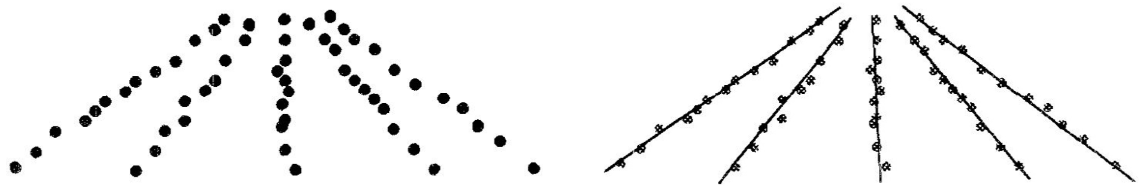


Figure 2.3. Example GPS guidance patterns (Heraud and Lange, 2009)

Autonomous guidance, navigation, and operation of agricultural machines begins to take shape with the addition of machine vision. Machine vision uses image-based recognition for feature identification that is used in decision making and vehicle guidance. Research and use of machine vision for agriculture vehicle guidance has been ongoing since the 1990s and continues to advance as image sensors and computational processing power improves each year (Hague et al., 2000). A camera is used to collect images that can be analyzed to determine the vehicle's surroundings, such as rows of crops or oncoming obstacles. Specific features in each image are determined in part by varying levels of brightness, color, and contrast. A basic example of row identification can be seen in Figure 2.4 where row lines are created using a black and white image. First, the brightness and contrast of the image pixels are used to identify the location of plants. With plant locations identified, the remaining pixel data is removed, leaving dark dots that represent plants (Figure 2.4(a)). Then row lines are created using regression fit of the dark dots. As the machine travels, the vanishing point and pattern will move, and this movement information is used to make steering or speed changes (Billingsley and Schoenfisch, 1997).

In addition to vehicle guidance, other applications of machine vision in agriculture include mapping, precision actuation, and plant phenotyping. These supplementary



(a) Plants appear as black dots (b) Row lines are regression fit image

Figure 2.4. Row identification from image (Billingsley and Schoenfisch, 1997)

functions allow an agricultural vehicle to not only have autonomous guidance and travel, but also autonomously perform operations and tasks. Examples include weed detection, crop health analysis, obstacle avoidance, and mapping of the environment (Pajares et al., 2016).

GPS and machine vision are not the only state-of-the-art navigation methods. Other common methods include inertia sensors, ultrasonic senors, encoders, and light detection and ranging (LiDAR). These equipment can be used in conjunction with GPS to provide plant-level control and navigation of agricultural vehicles. For example, LiDAR can be used to locate and identify apple trees in an orchard in order to automatically create an inventory of trees (Figure 2.5). LiDAR uses light pulses to measure distances and create a precise point cloud of the surrounding environment. By analyzing the points and distance data, trees can be recognized and counted (Bargoti et al., 2015).

2.3 Levels of Automation

A first step towards achieving autonomous agricultural vehicle operation begins with successful automatic navigation and guidance. As the history of farm vehicle guidance has been discussed above, it shows the progression of technology from basic mechanical methods to the complex computational approaches of present-day. The next phase is to implement automatic function and task performance for common applications for autonomous ground vehicles. It is helpful at this time to discuss the

Figure 2.5. Research ground vehicle traversing between two trellis rows and scanning with LiDAR (Bargoti et al., 2015)

various levels of automation and their capabilities. SAE (2018) defines six levels of automation for on-highway motor vehicles:

- Level 0: no driving automation
- Level 1: driver assistance
- Level 2: partial driving automation
- Level 3: conditional driving automation
- Level 4: high driving automation
- Level 5: full driving automation

Case IH (2018) has also developed definitions for five different levels of autonomous operation (Figure 2.6). This list is more applicable to agricultural vehicles and will be used for reference in this research. The ultimate goal for AAV operation is to achieve full autonomy. While this milestone has yet to be achieved in commercial applications, there is ongoing research and development in many different areas that show promise for the future. Examples of these uses of agricultural robots are discussed in the following section.

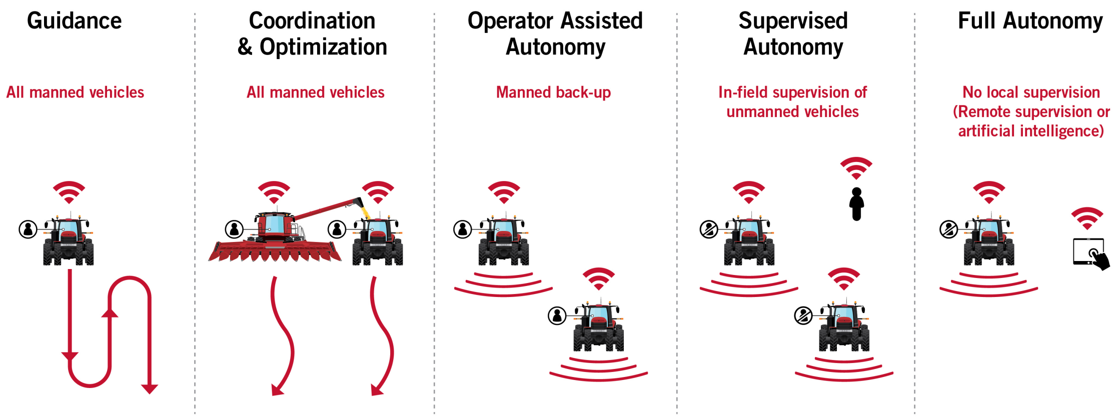


Figure 2.6. Levels of agricultural vehicle autonomy (Case IH, 2018)

2.4 Common Machine Applications for Ground-Based AAVs

2.4.1 Plant Detection, Phenotyping, and Monitoring

Precision agriculture uses site-specific knowledge for the purpose of doing the right thing, at the right place, at the right time (Bongiovanni and Lowenberg-Deboer, 2004). AAVs can be an integral part of this process by gathering information at a subfield level, thus directing appropriate tasks based on specific conditions. Plant detection, phenotyping, and monitoring provides insight into crop location, growth stages, and health. BoniRob is an autonomous vehicle platform for plant phenotyping that has been in development as a cooperation between industry and academia (Ruckelshausen et al., 2009). The vehicle is powered by four wheel hub motors and allows for additional sensors and accessories to be easily added (Figure 2.7). Weiss and Biber (2011) developed a novel BoniRob LiDAR sensor attachment for plant identification and localizing. By imaging crop rows, plants and weeds can be identified and catalogued based on their field location. This information can be stored in a central database for use with other farm tasks, such as spraying and harvesting.

Torres-Sospedra and Nebot (2014) recognized the need for reducing herbicide application in orange groves and have developed a system for weed identification and

Figure 2.7. BoniRob autonomous mobile platform (Bosch, 2017)

localization between rows. Weed detection was performed in a two stage operation. First, images were processed by identifying the main features: sky, soil, trees, and trunks. Second, weeds are identified by only looking in the areas labeled as soil. The identification process was completed through neural networks that continually trained and updated their algorithms. Weed location data could be used to analyze the effectiveness of existing weeding methods or be employed by a weeding AAV.

2.4.2 Soil Sampling and Mapping

Localized soil conditions are another integral aspect of precision agriculture. Examples of soil sampling and mapping AAVs include an articulated mid-sized ground vehicle that traverses a field and collects soil samples (Figure 2.8). Using guidance and mapping software, and operator determines field boundaries and specifies waypoints that direct the robots navigation path, along with specific sampling locations. Using the sampling data, a map can be built of various soil conditions across a given field (e.g., compaction, moisture level, nutrient and contaminant content, pH levels). Another example of automated soil sampling is the AutoProbe by Agrobotics. This implement samples at a given interval to provide accurate and consistent soil analysis, and uses GPS location data to store site information for further reference (Suprem et al., 2013). While the AutoProbe is merely an intelligent implement, it could easily be towed by an AAV to provide full autonomous operation.

Figure 2.8. Articulated steering soil sampling AAV (Väljaots et al., 2018)

2.4.3 Mechanical Weeding

Autonomous mechanical weed control shows great potential for decreasing labor costs and contributing to greater sustainability. Weeds are typically controlled through broad application of herbicide; however, this method can be unavailable for some farming operations (e.g., organic farming). Bakker et al. (2010) systematically designed an autonomous robot for mechanical weeding of sugar beet farming operations. The weeds are identified using an infrared light sensor and removed with a knife-equipped vertically spinning disc. Nørremark et al. (2012) developed an automatic tillage system for inter- and intra-row weed control. A small autonomous tractor traveled through a field using RTK-GPS navigation and engaged a cycloid hoe based on known plant locations from precision seeded crops. Tillett et al. (2008) developed another towed mechanical weeding implement that utilized a horizontally spinning disc for intra-row cultivation (Figure 2.9). By using machine vision, the position of the spinning discs were adjusted to account for weed location versus crop location. Additionally, the control scheme was able to adapt for crop spacing variability.

Figure 2.9. Machine vision rotary cultivator (Tillett et al., 2008)

2.4.4 Precision Spraying

Precision spraying may be one of the most attractive use cases for AAVs. The key feature is the ability to positively identify targets and intelligently apply the appropriate amount of solution (fertilizer or pesticide) in the most effective locations. Outcomes of precision spraying include decreased chemical usage, reduced cost, and improved safety of food products (Bonadies et al., 2016). Examples include work from Gonzalez-de Soto et al. (2016) where a commercial agricultural tractor was modified for autonomous operation and utilized a direct-injection patch spraying boom to apply herbicide for cereal crops. Weed patches were identified using on-board cameras and a controller automatically turned on specific sprayer nozzles at appropriate times. Field tests demonstrated treatment was applied to ~95% of the detected weeds while using 66% less product compared to a conventional spraying system.

Rowbot Systems is a startup company that partnered with Carnegie Robotics, LLC. to develop an AAV for intelligent nitrogen fertilizer application in corn fields

(Talbot, 2014). The vehicle is an articulated four wheeled machine that uses LiDAR and GPS to navigate between rows spaced 30 inch apart (Figure 2.10). They are currently deploying four machines in partnership with Growmark, Inc. with the aspirations of having 2,000 machines in the field by 2022. Their business model is to deploy a small number of machines and a recharge station to a field, allow the robots to work for 24 hours, and then pack them up and move on to the next field after their job is complete (Cavender-Bares, 2018).

Figure 2.10. Rowbot AAV (Grounds, 2014)

As mentioned previously, BoniRob is an autonomous vehicle platform that was originally developed for field-based crop phenotyping. However, additional research groups continue to develop add-on attachments, such as a precision sprayer (Scholz et al., 2014). With a working width of 1.5 m, a precision spray module was tested on row crops. The sprayer arm has 8 nozzles that can each be controlled for custom application needs to site-specific weeds.

2.4.5 Harvesting

Automating harvesting is an appealing concept, particularly when applied to high-value crops. Because labor makes up such a large component of these farming systems, AAVs show great promise in reducing necessary labor needs and therefore greatly decreasing costs. A review of unmanned ground vehicles by Bonadies et al. (2016) includes several examples of harvesting AAVs for use in high-value crops. Sakai et al. (2008) developed an automatic watermelon harvester that demonstrated the heavy lifting capabilities of mobile robots. The machine featured an overhung boom arm with adjustable manipulator grip. Field testing demonstrated results with ~87% success rate and averaged 14 s to pick and place a watermelon. While this was slower than a skilled worker (100% success rate and 10 s per watermelon), it shows promising results for future research.

De-An et al. (2011) designed and tested an autonomous apple harvesting robot that used an articulated arm with a spoon-shaped end-effector gripper. The tracked vehicle utilized GPS for orchard navigation and a vision-based module for the identification of apples. Indoor and outdoor tests demonstrated a success rate of 77% and and average harvesting time of 15 s per apple.

Iida et al. (2013) constructed an autonomous system for rice harvesting. A Mitsubishi VY50CLAM four-row combine was retrofit with sensors and controls to allow for autonomous navigation through rice paddy fields via RTK-GPS. While the machine did not have any special attachments or complicated manipulators, it demonstrates the possibilities that are feasible with AAVs.

2.5 Modeling of Agricultural Vehicles

As described in the previous section, research and application of AAVs have been demonstrated and are a growing area of interest and study. Yet, there is still an exceptional amount of effort remaining until AAVs become prevalent among agricultural operations. Common limiting factors contributing to the lack of widespread adoption and success of AAVs include low crop production efficiency and lack of economic justification (Bechar and Vigneault, 2016). Additionally, much of the research being completed tends to omit discussion of the design process that was used in the development of the robotic vehicles. These systematic design practices aid in the process of making well informed choices regarding the application and configuration of AAVs.

Roldán et al. (2018) reviewed current applications of robots in agriculture and found that few authors report or describe the design process of ground robots. While many design choices can be made by referring to existing technology or vehicles, the decisions on hardware and deployment will influence robot performance, complexity, efficiency, and cost. Similarly, Bac et al. (2014) reviewed harvesting robots for high-value crops and found that of the 50 harvesting robots analyzed, only six of the authors reported using systematic design methods. Furthermore, only four of the authors performed an economic analysis.

While there is an apparent lack of emphasis on modeling-based design, some research has been shown to utilize system analysis and discuss the economic feasibility of AAVs. Examples include Pedersen et al. (2006), who investigate the economic feasibility of replacing conventional agricultural vehicles with AAVs in three different applications: weeding in high value crops, field scouting of weeds in cereals, and grass cutting on golf courses. In all three applications, the costs and potential benefits of AAV use were compared with conventional machines. The economic model considered varying inputs such as initial capital investment, labor costs, working hours, energy consumption, speed, maintenance, and depreciation. The conclusions from these studies showed mixed results. Autonomous weeding demonstrated a ~15% reduction of cost compared to conventional methods as long as the depreciation period was greater than six years. Yet, autonomous weeding required more time in the field due to the sprayer's low capacity of only treating four rows simultaneously. Field scouting of weeds also proved to be ~20% less expensive so long as the cost of the machine remained below the estimated range of $20,000. Finally, golf course grass cutting proved to to be considerably more economical due to the elimination of high labor costs.

As mentioned earlier in Section 2.4.3, Bakker et al. (2010) systematically designed an autonomous robot for mechanical weeding for sugar beet farming operations. By breaking down the vehicle design process into different phases, the designer is forced to systematically analyze the application requirements and all proposed solutions. For example, one requirement was to determine where intra-row weeding has to be performed. Solutions to this requirement include seed mapping, identifying weeds via shape and color, pattern recognition, and spectral reluctance. Through careful evaluation of the proposed options, pattern recognition was chosen because it was reliable and could be used on other crops. The result of this design process approach was a four-wheeled vehicle with a diesel engine, hydraulic transmission, and four-wheel steering (Figure 2.11). While this method is not necessarily modeling-based, the resulting design has undergone thorough review and several iterations were proposed. This resulted in a vehicle that is not merely a retrofit of existing agricultural machinery, but a custom robot that is appropriate for the specific agricultural tasks.

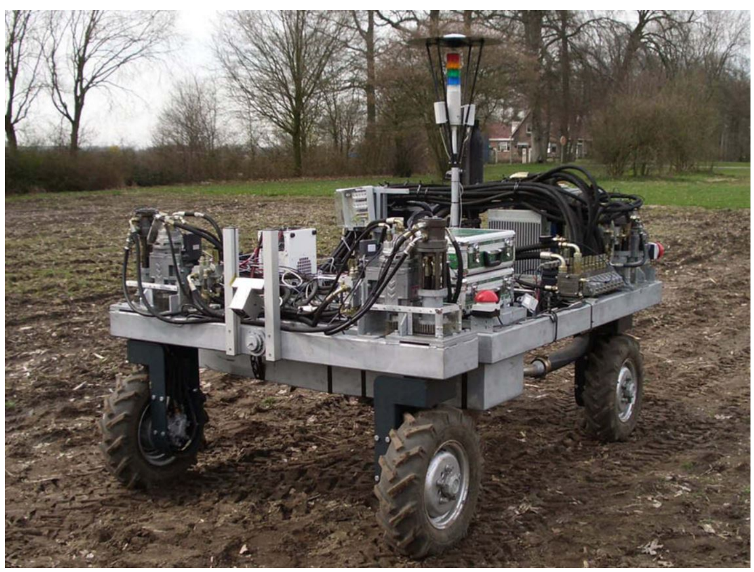


Figure 2.11. Autonomous vehicle platform for robotic weeding (Bakker et al., 2010)

The work by Väljaots (2017) is probably the closest example of an AAV design process that is established through modeling-based procedures. The useful aspect of this research is the development of an energy consumption model, which utilizes a typical vehicle dynamics model to calculate total power required for an unmanned ground vehicle. While this work did not directly use modeling outputs for vehicle design, it did develop a method for evaluating energy consumption and efficiency with direct application to AAVs.

Sopegno et al. (2016) developed a computational model that estimated energy requirements of *miscanthus x giganteus* production and transportation in Italy. The tool accounts for the energy requirements of each individual operation and compiles them into an overall energy demand. Specifically, the relationship between energy requirements, field area, and field-to-storage distance was explored. This model was built in order to provide results to be used in the design and evaluation of a specific agricultural production system. Rodias et al. (2017) continued this research with an extension to this model. This new computational tool was built for the analysis of multi-crop systems and the energy requirements and efficiencies associated therein. The specific example used looked at the production of *miscanthus x giganteus*, *Arundo donax*, and *switchgrass* in Italy. Once again, this model demonstrated its usefulness in evaluating the effects of different agricultural practices on energy requirements and machine efficiency. Although this research attempts to quantify and discuss energy requirements associated with various farming operations, its scope is limited and only focuses on conventional agricultural vehicles.

There is a need for an all-encompassing model that can be applied to the design and evaluation of AAVs. Although AAV research and applications are growing in popularity, the majority of work is based off of arbitrary design choices or simply adapted from existing conventional agricultural machines. The research presented in this proposal fills in this gap and assists in the design, management, and market adoption of AAVs. A simulation model to predict and quantify energy needs leads to a greater understanding of the design and capabilities of AAVs. The resulting energy requirement data would be directly used to evaluate the efficiency of AAVs. These efficiency metrics allow for unbiased analysis of the advantages or disadvantages associated with replacing and/or augmenting conventional agricultural vehicles with AAVs. The hypothesis among researchers is that AAVs will revolutionize agricultural practices and bring about more efficient and environmentally friendly farming methods. The goal of the research presented here is to test this theory using novel energy and efficiency models in order to discover the future potentials of AAVs.

3. ENERGY MODEL

The first objective of this research is to develop a simulation model of autonomous agricultural vehicle (AAV) energy requirements. This deterministic model follows standard methods of predicting and quantifying energy needs and energy expenditures of agricultural vehicles, particularly ground vehicles that operate primarily on row crops. This simulation model is not a full energy balance of agricultural processes. Rather, the model focuses on the various inputs necessary for autonomous and conventional agricultural vehicles to complete desired tasks. A greater understanding of the design and capabilities of AAVs can be known through the quantification of these energy requirements.

3.1 Energy Requirements of Farming Operations

There are four main energy inputs for agricultural vehicle field operations (Figure 3.1). The first input is the vehicle itself. Each agricultural vehicle and implement contributes this input through its embodied energy. Embodied energy of a vehicle (or implement) includes the energy of the raw materials used in the manufacturing process, and the energy to transport the vehicle from the manufacturer to the customer. Another field operation input is the vehicle's energy source. For conventional farm vehicles, this energy source is typically a petrochemical fuel, such as diesel. However, there are other energy sources available that could power a farm vehicle (e.g., batteries, biofuels, and fuel cells). A third input source is the agricultural material applied to the field. Example field operations that apply material include planting, spraying, and irrigation. The final energy input is the human labor necessary to complete a given field operation. Using these four energy inputs, in conjunction with the total time of operation, the total energy for a given agricultural operation is calculated.

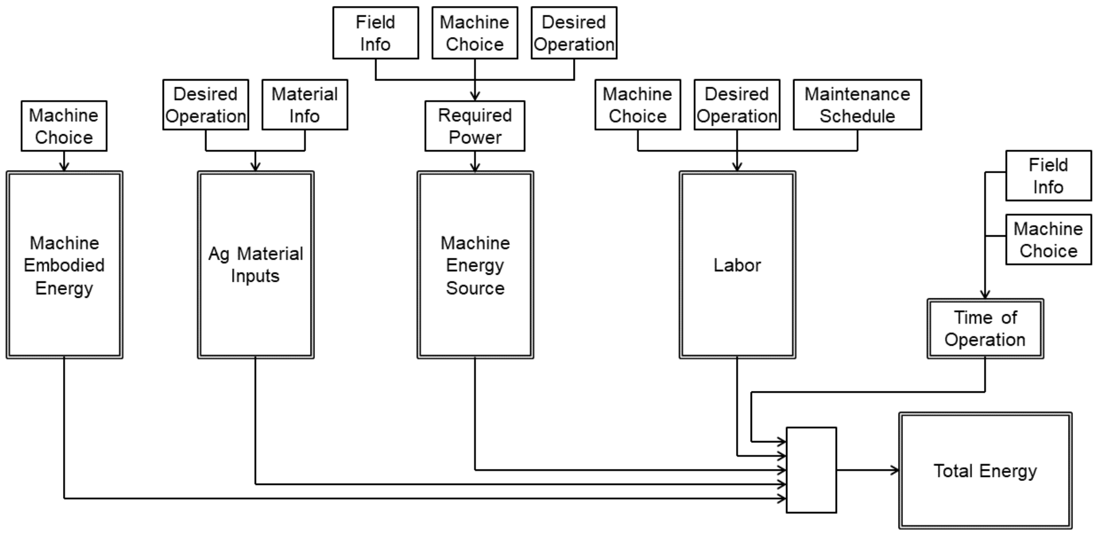


Figure 3.1. Four main energy sources

3.2 Operations of Machines

The operations and uses of agricultural field machines can generally be separated into three different types (Bochtis and Srensen, 2009):

1. Neutral material flow: no material flow into the field during operation (e.g., tillage, chopping)
2. Input material flow: material flows into the field during operation (e.g., planting, spraying, irrigation)
3. Output material flow: material flows out of the field during operation (e.g., harvesting)

These operation types give a framework for three generalized use conditions for agricultural field machines (Sopegno et al., 2016):

1. In-field operations: planting, spraying, harvesting, etc.
2. Roading operations: travel from farm-to-field, field-to-field, and field-to-farm
3. Biomass transport: material removed from field for further processing or sale

These three generalized vehicle operations serve as a method of organizing the energy model and help ensure that all energy sources are accounted for. In the following subsections, the energy model and methodology are discussed.

3.3 Energy Model Structure

The energy model was created in Microsoft Excel, and the model architecture is shown in Figure 3.2. The model is divided into different modules and uses user-input, along with prior module data, to generate an output at each step along the way.

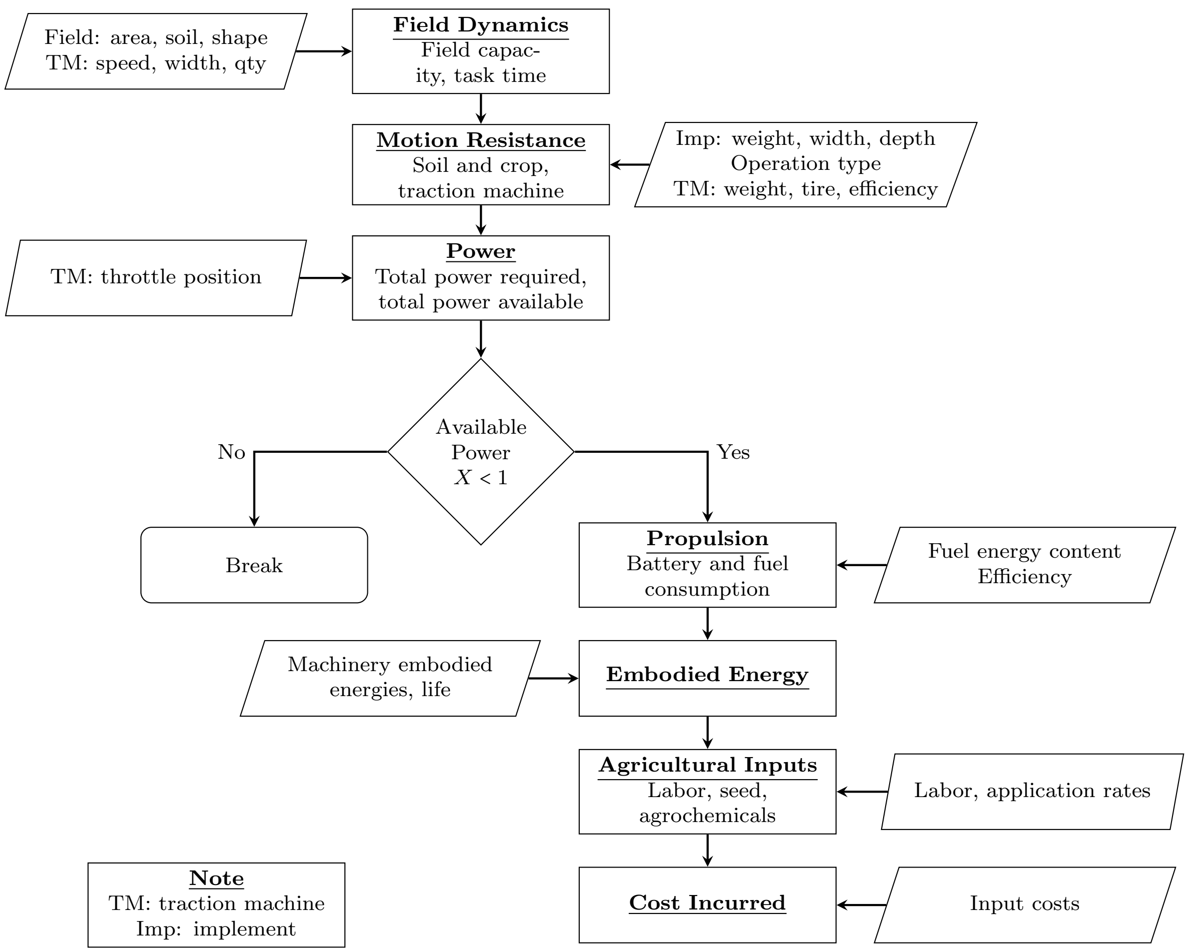


Figure 3.2. Structure of energy model

3.3.1 Field Dynamics Module

The field dynamics module calculates the field capacity and task time for a given operation. The total time for a given field operation is dependent on the implement working width, working speed, field efficiency, field area, and number of machines (e.g., swarm of autonomous vehicles). Field efficiency is the ratio between the actual productivity of a machine and the theoretical maximum productivity. Field efficiency accounts for the inability to utilize the theoretical implement working width, field characteristics, and lost time in the field. Common examples of lost time can include turning and idle travel, cleaning clogged equipment, machine adjustment, and in-field repair and maintenance. Field efficiency is not a constant value for a particular machine or throughout a given field operation. It varies with the shape and size of the field, pattern of field operation, crop yield, and other factors. All of these considerations lead to the calculation of field capacity (ASABE, 2015b; Hunt and Wilson, 2016):

$$C_a = \frac{swE_f n_{machines}}{10} \tag{3.1}$$

where C_a is the field capacity (ha/hr), s is machine travel speed (km/hr), w is implement rated working width (m), E_f is field efficiency (decimal), and $n_{machines}$ is the number of traction machines. While the user can choose any value for field efficiency and machine travel speed, typical ranges and values are automatically calculated based on the chosen field operation and soil type and are displayed as suggestions. These values can be found in ASAE D497.7, Clause 5 (ASABE, 2015a).

Using the calculated field capacity and the field area, the total time for a given field operation is found:

$$t_{field} = \frac{a}{C_a} \tag{3.2}$$

where a is the field area (ha).

3.3.2 Motion Resistance Module

The next module in the energy model quantifies the motion resistance associated with the soil/crops and traction machine. Soil and crop motion resistance (MR_{SC}) is the total force parallel to the direction of travel that is required to propel the implement (ASABE, 2015b). This does not take into account the motion resistance of the implement wheels, which is typically very small compared to the soil and crop motion resistance.

$$MR_{SC} = F_i(A + Bs + Cs^2)wT \tag{3.3}$$

where A, B, and C are implement-specific parameters given in ASAE D497.7 Table 1 (ASABE, 2015a), F_i is the soil texture parameter given in ASAE D497.7 Table 1 (ASABE, 2015a), and T is the tillage depth (cm).

Traction machine motion resistance (MR_{TM}) is the force required to overcome the rolling resistance of the traction machine tires (ASABE, 2015a).

$$MR_{TM} = W_{TM}\rho \tag{3.4}$$

where W_{TM} is traction machine weight (N) and ρ is motion resistance ratio (decimal). Based on experimental test results, the equation for motion resistance ratio is slightly different depending on tire type (Goering et al., 2003).

$$\rho = \begin{cases} \dfrac{1.0}{B_n} + 0.04 + \dfrac{0.5sl}{\sqrt{B_n}} & \text{bias ply tires} \\ \\ \dfrac{0.9}{B_n} + 0.0325 + \dfrac{0.5sl}{\sqrt{B_n}} & \text{radial ply tires} \end{cases} \tag{3.5}$$

where B_n is the mobility number (decimal) and sl is slip (decimal). Slip is not directly calculated because the traction machine engine speed and transmission gear ratios are not required for the model. This allows the model to be used for a broader range of agricultural vehicles, where transmission or engine information is lacking. Slip is the percentage difference between theoretical travel speed and actual travel speed, and it can be calculated through an iterative process using theoretical travel speed, drawbar pull from traction machine, and total draft. For the model presented in this work, slip is derived from the soil condition and assuming maximum tractive efficiency, as discussed in ASAE EP496.3 Section 3.3 (ASABE, 2015b) and shown in Table 3.1.

Table 3.1.
Optimum Slip Ranges, *sl* (ASABE, 2015b)

Soil Condition	**Slip (%)**
Concrete	4–8
Firm	8–10
Tilled	11–13
Soft	14–16

The mobility number is a dimensionless ratio and is calculated as follows (ASABE, 2015a):

$$B_n = \frac{CIbd}{W} \cdot \frac{1 + 5\frac{\delta}{h}}{1 + 3\frac{b}{d}} \tag{3.6}$$

where CI is the cone index for the soil (kPa), b is the unloaded tire section (m), d is the unloaded overall tire diameter (m), W is the dynamic wheel load normal to soil surface (N), δ is the tire deflection (m), and h is the tire section height (m).

Following the equations above, the total draft (i.e., total force) required to propel the traction machine and implement is reached:

$$D_{total} = MR_{SC} + MR_{TM} \tag{3.7}$$

3.3.3 Power Module

The total power required for the desired field operation (P_{op}) is the sum of all vehicle and implement power components converted to equivalent PTO power (ASABE, 2015b):

$$P_{op} = \frac{P_{db}}{E_m E_t} + P_{pto} + P_{hyd} + P_{el} \tag{3.8}$$

where P_{db} is the drawbar power (kW), E_m is the mechanical efficiency of the tractor's power train and transmission (typically 0.96 for tractors with gear transmissions), E_t is the tractive efficiency (see Table 3.2), P_{pto} is the required PTO power by the implement (kW), P_{hyd} is the required hydraulic power by the implement (kW), and P_{el} is the required electrical power (kW).

Table 3.2.
Tractive Efficiency, E_t (ASABE, 2015a)

Tractor Type	Tractive Condition			
	Concrete	Firm	Tilled	Soft
2WD	0.87	0.72	0.67	0.55
MFWD	0.87	0.76	0.72	0.64
4WD	0.88	0.77	0.75	0.72
Track	0.88	0.76	0.74	0.72

Drawbar power (kW) as required by the vehicle and implement is given by (ASABE, 2015b):

$$P_{db} = \frac{D_{total} s}{3600} \tag{3.9}$$

where s is the travel speed through the field (km/hr) and D_{total} is the total draft (N).

The PTO power (kW) that is delivered to the implement though the tractor's PTO shaft is given by (ASABE, 2015b):

$$P_{pto} = a + bw + cF_{mat} \tag{3.10}$$

where a, b, and c are implement specific parameters given in ASAE D497.7 Table 2 (ASABE, 2015a) and F_{mat} is the material feed rate (t/hr wet basis).

The hydraulic power (kW) required by the implement is given by (ASABE, 2015b):

$$P_{hyd} = \frac{pQ_{hyd}}{60000} \tag{3.11}$$

where p is fluid pressure (kPa) and Q_{hyd} is fluid flow rate (L/min).

The electrical power required by the implement or additional vehicle electronics (e.g., sensors and computers on an AAV) is given by:

$$P_{el} = \frac{iV}{1000} \tag{3.12}$$

where i is current draw (A) and V is voltage (V).

It is important to note that the engine power of the traction machine must be greater than total required power (Equation 3.8) in order to account for factors such as machine acceleration, changes in soil conditions and topography, and operator-related requirements (e.g., air conditioning, lighting). These power requirements must also be accounted for if they are significant in nature.

3.3.4 Propulsion Module

Using the current operation's equivalent PTO power requirement (Equation 3.8), the amount of energy necessary for propulsion can be calculated. The energy model presented in this work focuses on conventional diesel-powered agricultural vehicles as well as considering battery-powered agricultural vehicles. In future studies, this energy model could be expanded to incorporate other power sources (e.g., fuel cells or gasoline engines) or other powertrain architectures (e.g., hybridization).

3.3.4.1 Diesel-Power Vehicles

To calculate volumetric fuel usage of a diesel-powered agricultural vehicle, the specific fuel consumption and the time duration of a field operation are needed. The specific fuel consumption for a typical diesel engine working at or below maximum loading and operating at full and partial throttle is (ASABE, 2015a):

$$SFC_v = (0.22 + \frac{0.096}{X}) \cdot PTM \tag{3.13}$$

$$X = \frac{P_{op}}{P_{rated}} \tag{3.14}$$

$$PTM = 1 - \left[(N-1)(0.45X - 0.877)\right] \tag{3.15}$$

where SFC_v is volumetric specific fuel consumption (L/kW·hr), X is the fraction of equivalent power take-off power available, P_{op} is the equivalent PTO power required by the current operation (kW), P_{rated} is the traction machine's rated PTO power (kW), and N is the engine throttle ratio (i.e., at operating load, the ratio of partial throttle engine speed to full throttle engine speed). An alternative approach to calculate fuel consumption would be to follow the methods shown by Grisso et al. (2008) where tractor-specific coefficients are used from data published by the University of Nebraska Tractor Test Laboratory (NTTL). While that method is able to utilize test data for individual tractors, information is not available for all vehicles, certainly not for hypothetical, yet-to-be-built vehicles. The procedure presented above in Equations 3.13–3.15 is based upon NTTL data and is able to depict the effects of partial throttle and reduced loading; yet, it remains general enough to apply to a broad range of vehicles.

Using the calculated volumetric specific fuel consumption, the fuel consumption for the particular field operation is found:

$$Q_{fuel} = SFC_v \cdot P_{op} \tag{3.16}$$

where Q_{fuel} is the fuel consumption rate for a particular operation (L/hr).

In addition to fossil fuel, engine crankcase oil is also consumed and is related to tractor engine size. For a diesel engine, the lubrication consumption is given by (ASABE, 2015a):

$$Q_{lube} = 0.00059 P_{rated} + 0.02169 \tag{3.17}$$

where Q_{lube} is the volumetric specific lubrication consumption rate (L/hr).

Once the fuel consumption rate is determined, the total energy consumption rate associated with the consumed fuel from all the machines is given by:

$$E_{fuel} = \frac{u_{fuel} Q_{fuel}}{C_a} \cdot n_{machines} \tag{3.18}$$

where E_{fuel} is the energy rate of the consumed fuel (MJ/ha) and u_{fuel} is the energy density of the fuel (MJ/L).

The total energy consumption rate associated with the consumed lubrication oil from all the machines is given by:

$$E_{lube} = \frac{u_{lube} Q_{oil}}{C_a} \cdot n_{machines} \tag{3.19}$$

where E_{lube} is the energy rate of the consumed lubrication (MJ/ha) and u_{lube} is the energy density of the lubricant (MJ/L).

3.3.4.2 Battery-Powered Vehicles

While battery-powered agricultural machines are not yet a common component of conventional agricultural operations, they are slowly gaining in popularity. The energy model presented in this work focuses on simulating smaller electric agricultural vehicles, such as small tractors, utility vehicles, quad bikes, and experimental robotic machines. A common approach to electric vehicle modeling is to follow the energy flow shown in Figure 3.3. While efficiencies of individual components vary throughout an agricultural in-field operation (e.g. electric motor efficiency varies with speed and torque, and it also varies with motor type), constant efficiencies have been chosen based on published literature in order to reduce complexity and the required information regarding individual components of an electric vehicle (Hayes et al., 2011; Redpath et al., 2011; Hofman and Dai, 2010; Campanari et al., 2009; Mecrow and Jack, 2008; Williamson et al., 2006; Boglietti et al., 2003).

The energy flow begins as the vehicle's battery is charged at the charging station. This is equivalent to a refueling event for a diesel-powered vehicle. Once the battery's

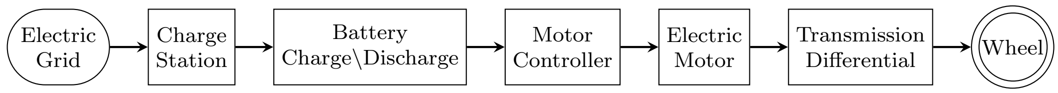


Figure 3.3. Electric vehicle energy flow

state of charge is high enough for the application (e.g., 90–100%), the vehicle travels to the field in order to complete the desired task. The amount of electrical energy consumed is shown below:

$$E_{elec} = \frac{3.6 P_{op}}{C_a \eta_{cs} \eta_{batt} \eta_{mc} \eta_{em} \eta_m} \cdot n_{machines} \tag{3.20}$$

where E_{elec} is the electrical energy consumption rate (MJ/ha), η_{cs} is the efficiency of the charging station (decimal), η_{batt} is the battery charge/discharge efficiency (decimal), η_{mc} is the motor controller efficiency (decimal), η_{em} is the electric motor efficiency (decimal), and η_m is the mechanical efficiency of the vehicle's transmission, differential, etc. (decimal).

3.3.5 Embodied Energy Module

Energy is directly consumed through the use of fuels, lubricants, and battery power, as shown above. However, indirect energy usage must also be taken into account in order to fully capture the total energy impact of farming operations. The agricultural machinery that are used for any given in-field operation have some amount of embodied energy associated with them. The raw material energy costs, manufacturing energy costs, and transportation energy costs of the machinery all account for the overall embodied energy. This parameter is typically reported in MJ/kg·yr or MJ/kg and allows for incremental indirect energy consumption to be attributed to each individual in-field operation, based on the amount of time spent per operation. Various studies provide estimates for embodied energy of agricultural machinery (Table 3.3) and can be used as reference for this energy model (Kitani et al., 1999; Wells, 2001).

Table 3.3.
Example Machinery Embodied Energy (Kitani et al., 1999)

Equipment	**Embodied Energy (MJ/kg)**
Tractor	138
Plow	180
Disc harrow	149
Planter	133
Fertilizer	129
Rotary hoe	148
Combine	116
*Recycling and re-use of old machinery is taken into account	

Each piece of machinery has a useful life associated with it, and every time that it is used and accumulates work-hours, energy is consumed based on the machinery's embodied energy and the amount of time spent on a particular operation. For example, a 7,000 kg tractor has a useful life of 16,000 hr, embodied energy of 138 MJ/kg, and is operating at a field capacity of 2.4 ha/hr. For each hectare covered, 25.2 MJ of embodied energy is consumed.

$$E_{emb} = \frac{e_{emb} m_{machinery} n_{machines}}{C_a t_{life}} = \frac{138\,\frac{MJ}{kg} \cdot 7000\,kg \cdot 1}{16000\,hr \cdot 2.4\,\frac{ha}{hr}} = 25.2\,\frac{MJ}{ha} \tag{3.21}$$

where e_{emb} is the embodied energy of the machinery (MJ/kg), $m_{machinery}$ is the mass of the machinery (kg), and t_{life} is the machinery's estimated life (hr). At the end of its useful life, machinery will typically get recycled and become a portion of the raw material for new equipment. This re-use of material is taken into account when determining the estimated embodied energy (Table 3.3).

It should be noted that the amount of consumed embodied energy calculated in Equation 3.21 is dependant upon generalized factors that can lead to uncertainties. For example, the standard life of a 4 wheel drive tractor is 16,000 hr (ASABE, 2015a);

yet, it is not uncommon for machines to be used past their standard predicted life. Additionally, the factors shown in Table 3.3 are based on estimations from evaluating the overall supply chain and life cycle of a machine and its raw materials. Even with these uncertainties, it is important to include the amount of consumed embodied energy in the overall energy analysis of agricultural operations. While this information may not be valuable to all stakeholders, such as design engineers and farmers, it provides big-picture information that could be useful to policy makers and helps to quantify the amount of energy being consumed.

3.3.6 Agricultural Inputs Module

The agricultural inputs module takes into account the input materials applied to the field and the labor associated with the in-field operation.

3.3.6.1 Input Materials

As discussed in section 3.2, input material flow operations add material to the field (e.g., planting and spraying). Just as machinery has an associated embodied energy, these added materials also have an energy content sequestered within them. This energy includes the amount required for production as well as the inherent energy of the product. The energy associated with input material flow operations is determined by the specified field operation and the particular material that is being applied. During a planting operation, seeds (or other propagation methods, such as rhizomes, bulbs, tubers, etc.) are planted at specific rates in order to achieve a desired plant population. While the planting rate may vary across a particular field, the average planting rate is used for this model. Embodied energy values for common production seeds in the U.S. are shown in Table 3.4 and the embodied energy consumption rate $E_{planting}$ is calculated in Equation 3.22.

Table 3.4.
Embodied Energy of Production Seed in the U.S. (Pimentel, 2009; Kitani et al., 1999)

Seed	Embodied Energy (MJ/kg)
Corn	104
Wheat	15
Rice	17
Soybeans	34

$$E_{plant} = \frac{r_{plant} e_{plant}}{\rho_{plant}} \tag{3.22}$$

where r_{plant} is the planting rate (seeds/ha), e_{plant} is the embodied energy of the planting material (MJ/kg), and ρ_{plant} is the density of the planting material (seeds/kg).

The application of agrochemicals is a large contributor of energy consumption in agriculture. Examples of agrochemicals applied to a field include fertilizers and pesticides. Similar to planting operations, the application of agrochemicals can vary throughout a field; however, the average application rate is used for this model.

$$E_{fert} = r_{fert} e_{fert} \tag{3.23}$$

$$E_{pest} = r_{pest} e_{pest} \tag{3.24}$$

where r_{fert} is the fertilizer application rate (kg/ha), r_{pest} is the pesticide application rate (kg/ha), e_{fert} is the embodied energy of the fertilizer (MJ/kg), and e_{pest} is the embodied energy of the pesticide (MJ/kg). Example embodied energy values of agrochemicals are shown in Table 3.5. The product values include the energy used for obtaining raw material, production of product, and distribution to customers.

3.3.6.2 Labor

The labor associated with in-field operations has a measure of energy that is considered in the energy model presented in this work. It is the amount energy consumed

Table 3.5.
Agrochemical Embodied Energy (Kitani et al., 1999)

Product	**Embodied Energy (MJ/kg)**
Nitrogen Fertilizer	78
Phosphorus Fertilizer	17
Potassium Fertilizer	13
2,4-D	85
Glyphosate	454

by agricultural workers during the completion of their tasks. In conventional industrialized agricultural operations, human labor is needed for each task, commonly for machine operation and maintenance. In future farming operations, the need for labor will decrease as AAVs become more prevalent. The responsibilities of human workers will shift from directly operating machinery (e.g., one worker for each vehicle), to supervising unmanned vehicles or a whole swarm of machines. This in turn will decrease the amount of workers and labor required to complete a task.

The assessment and quantification of the amount of energy consumed in human labor is a debatable issue for researchers. Methods and results vary widely depending on the specified criteria and system constraints (Aguilera et al., 2015). While the amount of energy associated with human labor is small compared to other contributors (e.g., machinery), it is still a part of the overall energy assessment of agricultural operations. This is especially true when considering the implications of reducing human labor because of the increase of autonomous machinery.

There are several common methods of calculating the amount of energy expended by human labor, and Aguilera et al. (2015) provide a thorough discussion of each method. The various methods range from assessing muscular power output of a worker, to accounting for dietary energy, to analysing the entirety of energy needed to support the lifestyle pattern of a worker and their family. Likewise, the value assigned to labor energy consumption ranges from 0.3 MJ/hr to 181 MJ/hr, depending on the system boundaries and constraints. However, the majority of agricultural energy analysis research follows the dietary energy consumption method. This approach assess the energy metabolic requirements of the laborer and has a value of 2.2 MJ/hr (Aguilera et al., 2015).

Along with the energy consumption rate of labor, the amount of work-hours for each operation must be specified. In a conventional agricultural in-field operation, a worker's time will primarily be consumed with operating a traction machine, such as a tractor, sprayer, or combine. This value of time was calculated in Equation 3.2. In addition to this time, there will be pre- and post-operation time spent by the worker completing other tasks related to the completed operation, such as travel, refueling, and daily machine service. There are few documented studies, data, or standards exploring the amount of non-field time that is required for an in-field operation. Much of the research discussing labor hours provides a comprehensive view of work-hours as they relate to an entire growing season. For example, Pimentel and Pimentel (2008) discuss the amount of labor required per hectare for U.S. production corn (11.4 hr), soybean (7.1 hr), wheat (7.8 hr), rice (24 hr), and other crops. Yet, their numbers do not separate out the time spent for each in-field operation. This method is repeated again and again by other researchers and they usually base their findings on government labor statistics or surveys of farming operations (NASS, 2018; Ibarrola-Rivas et al., 2016; Hunt and Wilson, 2016; Pimentel, 2009; Ali and McBride, 1994). Other work will discuss the issue of total labor time versus field machine time, but they make generalized claims about the amount of time spent out of the field. For example, Edwards (2015) estimates that actual labor hours exceeds field machine hours by 10–20%. while this estimation may work for some instances, it is an over-simplistic approach that is not applicable to varying situations. In large field sizes, the long field time would artificially inflate the amount of non-field labor time. Alternatively, small field sizes have short machine field times and could underestimate the amount of non-field labor that is required.

With the absence of useful data and research on labor time consumed on non-task activities, the approach taken in this research is to equate the amount of work-hours to the total time given for a field operation, as calculated in Equations 3.1 and 3.2. Introduced within these equations is field efficiency E_f, which is the ratio of theoretical field time (machine operating at ideal forward speed using its full width of action) to total time spent in the field. This efficiency factor is tabulated within ASABE D497.7, where a typical value is indicated along with a common range (ASABE, 2015a). Hunt and Wilson (2016) outline six items that are included within field efficiency:

1. Theoretical field time
2. Turning time and time crossing grass waterways
3. Time to load or unload machine containers, if not done on-the-go
4. Machine adjustment time, if not done on-the-go
5. Maintenance time (refueling, lubrication, chain tightening, etc., if not done on the go; not including daily servicing)
6. Repair time (time spent in the field to repair or replace inoperable parts)

As seen in the list above, there are several items that are directly related to work-hours being spent on non-task activities. While it would be ideal to capture the pre- and post-task labor times, the method settled upon is sufficient for this research. Additionally, this highlights the need for further research exploring the direct and quantifiable link between total required labor and task time, especially how it relates to emerging autonomous vehicle technologies.

The equations for calculating total labor time are different for conventional and AAV operations. In conventional operations each machine is directly controlled by an operator at all times. The equation for conventional total labor time is shown below.

$$t_{labor,conv} = t_{field} \tag{3.25}$$

where t_{field} is the total time spent in-field for a given operation (hr). For AAV operations each machine is able to operate without the need for direct human intervention or control. The level of human labor required is based on the level of autonomy of the AAV. Figure 2.6 shows general levels of autonomy for agricultural machines. This present research adopts a level of autonomy that is a hybrid between Supervised Autonomy and Full Autonomy. During a normal work day, the AAVs are supervised in the field. The length of a normal work day is set at 12 hr. This value is based on farmer interviews where a common in-field work day can range from 10-14 hr. If the task time (t_{field}) is longer than 12 hr, then the AAVs will continue operation un-supervised until the start of the next work day. The equation for AAV total labor time is shown below.

$$t_{labor,AAV} = \frac{n_{machines}}{n_{MpO}} \left\{ 12\,hr \cdot INT\left[\frac{t_{field}}{24\,hr}\right] + MIN\left[MOD\left[\frac{t_{field}}{24\,hr}\right], 12\,hr\right]\right\} \tag{3.26}$$

where n_{MpO} is the number of machines per operator (decimal), $INT[\,]$ returns a number rounded down to the nearest integer, $MOD[\,]$ returns the remainder, and $MIN[\,]$ returns the minimum argument. For example, if the total task time is 16 hr, the total labor time is 12 hr (the remaining four hours are completed unsupervised); if the total task time is 28 hr, the total labor time is 16 hr (12 hr supervised + 12 hr unsupervised + 4 hr supervised). Once the labor time is determined, the labor energy consumption rate can be calculated.

$$E_{labor} = \frac{t_{labor} r_{labor}}{a} \tag{3.27}$$

where t_{labor} is the total labor time for a given field operation (hr), r_{labor} is labor energy rate for a worker (MJ/hr), and a is the field area (ha).

3.3.7 Cost Incurred Module

The final module of the energy model calculates the financial cost of the four main inputs and allows for an alternative perspective on the amount of inputs required to complete a given in-field operation. The previous modules focused on calculating the energy requirements (in terms of MJ/ha) for a given in-field task. Analyzing the financial cost of an operation (in terms of $/ha) allows for a more thorough comparison between different machine configurations and can help illuminate any advantages or disadvantages of utilizing AAVs.

The cost function for the amount of propulsion power required (C_{prop}) by either a fossil fuel traction machine or an electric traction machine is as follows.

$$C_{prop,fossil} = \frac{E_{fuel} p_{fuel}}{u_{fuel}} \frac{E_{lube} p_{lube}}{u_{lube}} \tag{3.28}$$

$$C_{prop,elec} = \frac{E_{elec} p_{elec}}{3.6} \tag{3.29}$$

where p_{fuel} is the fuel price (\$/L), p_{lube} is the lubricant price (\$/L), u_{fuel} is the fuel energy density (MJ/L), u_{lube} is the lubricant energy density (MJ/L), and p_{elec} is the price of electricity (\$/kW·hr).

The cost function for machinery use is seen below.

$$C_{mach} = \left[\frac{p_{TM}}{t_{life,TM}} + \frac{p_{imp}}{t_{life,imp}} \right] \frac{n_{machines}}{C_a} \tag{3.30}$$

where p_{TM} is the traction machine purchase price (\$), p_{imp} is the implement purchase price (\$), $t_{life,TM}$ is the traction machine estimated life (hr), and $t_{life,imp}$ is the implement estimated life (hr). This equation uses a simple linear relationship between the life of the machine and the purchase price in order to generate a dollar-per-hectare value. A more detailed and nuanced approach would be to calculate the total cost of ownership for the machinery. This method includes information regarding the cost of machinery depreciation, interest, insurance, taxes, and housing/maintenance facilities. While the total cost of ownership approach will produce a more accurate estimation of costs, it also requires more details on the machinery and its usage, such as: age of machine when purchased, current age of machine, accumulated hours of use, estimated annual use, interest rate, and tax rates (Edwards, 2015). Repair and maintenance costs, as described in ASABE EP496.3 Section 6.3.1 (ASABE, 2015b), are also not currently included in the model, which can add significant costs to the machinery depending on the length of ownership and use of a vehicle.

The approach of the model presented herein is to capture the relevant processes and costs, while understanding that some generalizations will have to be made. The additional information required for estimating total cost of ownership would hinder the modeling process and is outside the desired scope of this research at this time. Future revisions and updates to the energy and cost model should include these added economic considerations.

The cost function for input material usage is:

$$C_{matl} = p_{plant}r_{plant} + p_{fert}r_{fert} + p_{pest}r_{pest} \tag{3.31}$$

where p_{plant} is the planting material price (\$/kg), p_{fert} is the fertilizer price (\$/kg), and p_{pest} is the pesticide price (\$/kg).

Finally, the labor cost function is:

$$C_{labor} = \frac{p_{labor}t_{labor}}{a} \tag{3.32}$$

where p_{labor} is the labor wage (\$/hr).

3.4 Limitations of the Model

The model presented in this chapter simulates the energy requirements of agricultural operations and can be applied to conventional or autonomous vehicles. The purpose of building the model is to investigate the various inputs and energy necessary for autonomous and conventional agricultural vehicles to complete desired tasks. By quantifying these energy requirements, a greater understanding of the design and capabilities of AAVs can be known.

While this model is able to quantify energy and financial costs, it is important to note some of the inherent limitations of the model. First, the model outputs are only as good as the inputs that are provided. For the conventional operations, reliable inputs can be found using manufacturing data, standards, published material, and farmer interviews. This is not the case with some of the AAV inputs. Because AAVs are not readily available or in use today, some generalizations or estimations must be made. Examples include the machine purchase price, vehicle weight, or field efficiency. Useful life is another important parameter that is especially difficult to predict for

AAVs because there is not long term data to support the typical life of AAVs. In addition to vehicle longevity, AAVs would have sensors or technologies that could become outdated and need repaired or replaced. Furthermore, electric AAVs have battery packs with a finite amount of life, and the energy and costs of replacement are currently not captured within the model.

The model does not account for pre- and post-operation labor time required for each task. As discussed in Section 3.3.6.2, because of the absence of useful data and research on non-task labor time this model has omitted the amount of time spent out of the field on other activities. Examples include field-to-field travel time, daily service, organization and planning, maintenance and repair, and others. Without additional reliable data, it is hard to give a definitive value to how much time is spent on non-task activities. This highlights the need for more research on agricultural labor time that could include farmer questionnaires or focus group sessions. Additionally, the logistics of planning and organizing a large number of AAVs would not be a trivial task. The effort and cost associated with this is also not captured in the model presented above, yet it could be significant and is worth exploring in the future.

Another limitation of the model is the financial analysis of the total cost of ownership for the machinery. Additional required input parameters include (but are not limited to): age of machine when purchased, current age of machine, accumulated hours of use, estimated annual use, interest rates, tax rates, and repair and maintenance factors. Additional financial analysis would provide a more complete picture of the true costs by providing information and costs pertaining to depreciation, taxes and insurance, repair and maintenance, and investment values. In addition to repair and maintenance costs, the embodied energy associated with repaired or replacement parts is not included in this model. Future revisions and updates to the model should include all of these considerations.

Finally, the model does not currently have the flexibility to analyze non-traditional machine configurations. An example of this would be a conventional machine working in tandem with a few smaller AAVs or multiple sized AAVs working together. These configurations could prove to be a more effective use of AAVs and would be worth investigating in the future. Likewise, the model is not currently able to analyze non-traditional vehicle architectures, such as hybrid machines. Hybrid machines could include a combination of electric, fossil fuel, fuel cell, or other power sources. The ability to analyze these types of machines could be added to the model during future work and could reveal more efficient methods of providing machinery propulsion.

3.5 Model Sensitivity Analysis

Along with considering the limitations of the model, a sensitivity analysis is a helpful procedure that can highlight any inputs that could have a large influence on output values. For the sensitivity analysis, a sample farming operation has been chosen to provide a baseline. In conventional Midwest U.S. corn and soybean farming operations, fertilizer is applied following the harvest (either in the fall or the spring). The machinery for the example operation is a 187 kW (250 hp) tractor traveling 10.5 km/hr (6.5 mi/hr) with a field efficiency of 65% (e.g., John Deere 8295R T3 pulling a FAST 8300 liquid fertilizer applicator). The UAN28% application rate is 280 L/ha (30 gal/acre). The full list of input parameters for the baseline case is shown in Appendix A.1. The two main outputs of the model are the energy consumption (MJ/ha) and cost consumption ($/ha). Tables 3.6 and 3.7 show the results of the baseline conventional fertilizing operation.

Table 3.6.
Sensitivity Analysis - Baseline Fertilize - Energy Consumption

Operation	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
Fertilize	218	134	7,800	0.3	8,153

Table 3.7.
Sensitivity Analysis - Baseline Fertilize - Cost

Operation	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Fertilize	3.62	7.74	78.00	1.92	91.28

As described in Section 3.4, the model outputs are only as good as the inputs that are provided. In the subsections that follow, sensitivity analysis is performed on several inputs in order to demonstrate their influence on energy and cost consumption.

3.5.1 Field Efficiency

Field efficiency (E_f) is the ratio of theoretical field time (machine operating at ideal forward speed using its full width of action) to total time spent in the field. This efficiency factor is tabulated within ASABE D497.7, where a typical value is indicated along with a common range (ASABE, 2015a). Field efficiency is affected by machinery turning time, machine adjustments, in-field repair and maintenance, and more. Tables 3.8 and 3.9 show the effects of varying E_f. The baseline value of E_f is 0.65, and it is varied ±0.15 or ±23% (these limits were chosen based on the published ranges). When E_f is decreased 23% (i.e., less efficient in the field), the propulsion and machinery consumptions increase ≈30%; when increased 23%, the propulsion and machinery consumptions decrease ≈18%.

3.5.2 Machinery Estimated Life

Machinery life (t_{life}) is the estimated useful lifetime of the machine. This value is tabulated within ASABE D497.7 (ASABE, 2015a). However, it is not uncommon for machines to be used past their standard predicted life. The baseline values for the traction machine life and the implement life are 16,000 hr and 1,200 hr, respec-

Table 3.8.
Sensitivity Analysis - Field Efficiency - Energy Consumption

E_f	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
0.50	284	175	7,800	0.4	8,259
0.65	218	134	7,800	0.3	8,153
0.80	177	109	7,800	0.2	8,087

Table 3.9.
Sensitivity Analysis - Field Efficiency - Cost

E_f	**Cost (\$/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
0.50	4.71	10.07	78.00	2.50	95.28
0.65	3.62	7.74	78.00	1.92	91.28
0.80	2.94	6.29	78.00	1.56	88.79

tively. Tables 3.10 and 3.11 show the effects of varying t_{life}. Only machinery energy consumption and cost consumption are affected by t_{life}. When t_{life} decreases 10%, consumption increases ≈11%. When t_{life} increases 10%, consumption decreases ≈9%.

3.5.3 Machinery Mass

The mass/weight of machinery can be found by referencing the specifications sheet provided by the machinery manufacturer. This data is readily available for conventional machines; however, estimations have to be made for AAVs. Tables 3.12 and 3.13 show the effects of varying the machinery mass. Very little effect is seen by changing the machinery mass ±10%. The propulsion energy and cost consumption changes ≈2%. Changing the machinery mass ±10% also effects the machinery embod-

Table 3.10.
Sensitivity Analysis - Machinery Life - Energy Consumption

t_{life}	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
-10%	218	149	7,800	0.3	8,168
Baseline	218	134	7,800	0.3	8,153
+10%	218	122	7,800	0.3	8,141

Table 3.11.
Sensitivity Analysis - Machinery Life - Cost

t_{life}	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
-10%	3.62	8.61	78.00	1.92	92.15
Baseline	3.62	7.74	78.00	1.92	91.28
+10%	3.62	7.04	78.00	1.92	90.58

ied energy consumption ±10%. This is expected since machinery embodied energy is directly proportional to machinery mass (see Equation 3.21).

Table 3.12.
Sensitivity Analysis - Machinery Mass - Energy Consumption

Mass	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
-10%	214	121	7,800	0.3	8,136
Baseline	218	134	7,800	0.3	8,153
+10%	222	148	7,800	0.3	8,171

Table 3.13.
Sensitivity Analysis - Machinery Mass - Cost

Mass	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
-10%	3.56	7.74	78.00	1.92	91.22
Baseline	3.62	7.74	78.00	1.92	91.28
+10%	3.69	7.74	78.00	1.92	91.35

3.5.4 Other Inputs

There are many other inputs that can be shown to have direct effects on the model outputs. Propulsion energy and cost consumption is the least likely output that can be effected by a single input because of the numerous parameters and equations used to describe those values. On the other hand, machinery and material energy and cost consumption are highly dependent on individual inputs, as shown in Section 3.3. This is particularly troublesome because of the generalizations and estimations made with embodied energy input parameters. The uncertainties and high sensitivity of embodied energy consumption must be taken into account when making conclusions and recommendations based on the model outputs.

4. SIMULATION AND APPLICATION OF MODEL

In this chapter, the energy model will be demonstrated using a pre-defined scenario of a typical row-crop farming operation in the Midwest U.S. The purpose of the case study is to complete a comparison between a conventional crop production operation and operations that have implemented autonomous machines. There are many different configurations and combinations that can be selected when comparing different farming operations. For this research, four general vehicle configurations have been chosen, based on the traction machine size: large tractor (e.g., greater than 60 kW), small tractor (e.g., less than 60 kW), utility vehicle (e.g., John Deere Gator), and smaller machines (e.g., single row machines). An example of how different machine architectures could be compared is shown in Table 4.1. In addition to the vehicles described in Table 4.1, each type of autonomous vehicle could operate individually or as a member of a fleet of other autonomous vehicles.

The case studies that follow will demonstrate how to use the energy model to compare the different input requirements between conventional and autonomous agricultural operations. First, the energy model will be used to compare a whole farm operation consisting of fertilizing, spraying, planting, and harvesting. Three different machine configurations will be analyzed: using all conventional large machines, using all autonomous large machines, and using all autonomous smaller machines (e.g., ≈55 kW tractor). Next, crop production operations will be compared on an individual basis. For example, as seen in Table 4.1, there are five different machine types that could be used for a spraying operation (one conventional and four autonomous).

Table 4.1.
Example General Categories for Comparison

Operation	**Conventional**	**Autonomous**
Fertilizing	Large tractor, wide implement	Large tractor, wide imp. Small tractor, narrow imp.
Spraying	Large self-propelled sprayer	Large self-propelled sprayer Small tractor with attachment Utility vehicle with attachment Single-row machine
Planting	Large tractor, wide planter	Large tractor, wide planter Small tractor, narrow planter Utility vehicle with attachment Single-row machine
Harvesting	Large self-propelled combine	Large self-propelled combine Small self-propelled combine

4.1 Crop Production Description

Conventional crop production operations in the Midwest U.S. are mainly geared toward corn and soybeans. No two farming operations are alike, and there are many different variables that could be chosen when specifying a typical farm (e.g., farm size, type of crops planted, number of machines, size of machines, etc.). In order to develop a generic Midwestern farming operation, practices and specifications were selected based on interviews with farmers, information from university extension offices, and other published guidelines. A common farm size is roughly 607 ha (1,500 acre), and it is typical to allocate half the land to corn and half to soybeans. These case studies will focus on corn production with a total field area of 300 ha (741 acre). The four main operations are no-till planting, fertilizer application, pesticide spraying, and harvest. A general timeline of operations is shown below.

- Fall/Spring: post-harvest fertilizer
- Spring: pre-plant pesticide
- Spring: no-till planting
- Spring: post-emergence pesticide
- Fall: harvest

4.1.1 Conventional Machinery Sensitivity Analysis

The process of deciding upon a generic farming operation requires assumptions and generalizations to be made regarding the location, total field size, machinery, and operations. While there was general consensus regarding the fertilizing and harvesting operations, the machinery used for the pesticide and planting operations need closer examination. A common vehicle for applying pesticide is a self-propelled sprayer. These machines are able to cover large areas because of their wide booms and fast travel speeds. The total farm size in this example case study may not be quite large enough to justify a common self-propelled sprayer with a 30.5 m (100 ft) boom. In Tables 4.2 and 4.3 below, three machines are compared with each other. The first machine is a 183 kW (245 hp) self-propelled sprayer with a 30.5 m (100 ft) boom (e.g., John Deere 4730). The second machine is a 129 kW (173 hp) self-propelled sprayer with a 18 m (60 ft) boom (e.g., John Deere R4023). The third machine is a 55 kW (74 kW) tractor pulling a 12.2 m (40 ft) boom sprayer (e.g., John Deere 5085E tractor pulling a FAST Big Wheel sprayer). In terms of energy consumption, the third option makes the most sense. This is mostly due to the lower propulsion energy required. When looking at cost consumption, the large self-propelled sprayer has a lower cost-per-field-area. Since the large self-propelled sprayer is able to travel quickly and has a wide boom, the amount of time spent in the field is very short. A downside of large self-propelled sprayers is their high cost. With a price over $350,000, it is hard to justify purchasing this machine for a farming operation with only 607 ha (1,500 acre). While the smaller option costs more to operate, its lower initial capital cost of about $120,000 makes it much more appealing.

Table 4.2.
Conventional Machinery Energy Analysis - Spraying

Width (m)	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
30.5	39	14	48	0.1	100
18	48	19	48	0.1	115
12.2	27	17	48	0.2	92

Table 4.3.
Conventional Machinery Cost Analysis - Spraying

Width (m)	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
30.5	0.65	2.92	9.24	0.47	13.28
18	0.81	3.45	9.24	0.80	14.30
12.2	0.48	5.33	9.24	1.68	16.72

A similar analysis has been performed for the planting operation. In Tables 4.4 and 4.5, three planter configurations are compared with each other. For all three configurations, the traction machine is a 187 kW (250 hp) tractor (e.g., John Deere 8295R T3). The three different planters used are a John Deere 1795 16 row planter, a John Deere 1775 12 row planter, and a John Deere 1725NT 8 row planter. In terms of energy, the 16 row planter configuration has the lowest consumption. With its wide implement, this configuration is able to quickly cover all the land area. The configuration with the lowest cost consumption is the 12 row planter at 309.50 \$/ha. Because all three configurations are using the same traction machine, it is important to consider the initial capital cost of the planter. An advantage of using a large 16 row planter is the ability to quickly complete the planting task, which can be especially important when inclement weather is a factor. However, with a price just over \$200,000, the 16 row planter is about 60% more than the 12 row planter and about 125% more than the 8 row planter. For this sample case scenario, the 12 row planter will be used. While it has a higher initial cost, its lower operating cost and faster task completion time make it more appealing.

Table 4.4.
Conventional Machinery Energy Analysis - Planting

No. of Rows	Energy Consumption (MJ/ha)				
	Propulsion	Embodied		Labor	Total
		Machinery	Material		
16	170	187	1,722	0.3	2,079
12	202	200	1,722	0.5	2,125
8	257	231	1,722	0.7	2,210

Table 4.5.
Conventional Machinery Cost Analysis - Planting

No. of Rows	Cost (\$/ha)				
	Propulsion	Machinery	Material	Labor	Total
16	2.87	24.00	281.45	2.36	310.68
12	3.43	21.46	281.45	3.15	309.50
8	4.39	24.49	281.45	4.73	315.06

4.2 Whole Farm Operation Study

4.2.1 Conventional Agricultural Operation

Following the fall harvest, fertilizer is applied to the field in the form of liquid nitrogen fertilizer (UAN28%). This allows for soil nutrients to be replenished in order to aid in the growth of the next season's crops. Nitrogen can be applied in the fall after the harvest or in the spring prior to planting. By applying fertilizer in the fall, there is one less task to complete in the springtime and can allow planting to occur earlier. However, for the purpose of this model, the timing does not affect the results. The machinery for this operation is a 187 kW (250 hp) tractor traveling 10.5 km/hr (6.5 mi/hr) with a field efficiency of 65% (e.g., John Deere 8295R T3 pulling a FAST 8300 liquid fertilizer applicator). The UAN28% application rate is 280 L/ha (30 gal/acre). Using a UAN28% density of 1.27 kg/L (10.6 lb/gal), r_{fert} is set at 100 kg N/ha (89 lb N/acre).

For this no-till corn production operation, it is important to eliminate weeds prior to planting. This is done in the spring with a 2,4-D burndown in-field operation. 2,4-D was chosen to be applied using a 55 kW (74 hp) tractor pulling a 12.2 m (40 ft) boom sprayer traveling 11.2 km/hr (7 mi/hr) with a field efficiency of 65% (e.g., John Deere 5085E tractor pulling a FAST Big Wheel sprayer). The application rate is 0.50 lb ai/acre (0.56 kg ai/ha).

Next, corn is planted in 30 inch rows using a 187 kW (250 hp) tractor pulling a 12 row planter traveling 8 km/hr (5 mi/hr) with a field efficiency of 65% (e.g., John Deere 8295R T3 pulling a John Deere 1775 12 row planter). The average population rate for the seeding operation is 82,780 seeds/ha (33,500 seeds/acre).

After planting has finished, the final springtime in-field operation is a post-emergence pesticide in order to control weeds. This weed control is beneficial because it reduces competition between crops and weeds, and it will lead to higher yields. Once again, 2,4-D is applied using a 55 kW (74 kW) tractor pulling a 12.2 m (40 ft) boom sprayer traveling 11.2 km/hr (7 mi/hr) with a field efficiency of 65% (e.g., John Deere 5085E tractor pulling a FAST Big Wheel sprayer). The application rate is 0.56 kg ai/ha (0.50 lb ai/acre).

Finally, harvest takes place in the fall after the growing season. The traction machine is a 240 kW (320 hp) combine harvester with a 12 row corn head traveling 6.6 km/hr (4 mi/hr) with a field efficiency of 70% (e.g., Gleaner S96).

A summary of the input parameters for the conventional agricultural operation is shown in Table 4.6. Output results in terms of energy consumption (MJ/ha) and cost ($/ha) are shown in Tables 4.7 and 4.8. Appendix A.1 contains all input values used for this analysis.

Table 4.6.
Conventional Agricultural Operation Inputs

Name	**Units**	**Fertilize**	**Herbicide**	**Planting**	**Harvest**
Operating Speed	[km/hr]	10.5	11.3	8	6.6
Field Eff.	[%]	65	65	65	70
Rated Width	[m]	11.4	12.2	9.1	9.1
TM Drive	[-]	MFWD	MFWD	MFWD	2WD
TM Throttle	[%]	80	75	80	100
TM Rated Power	[kW]	187	54	187	240
TM Mass	[kg]	11,678	4,205	11,678	23,000
TM Emb. Energy	[MJ/kg]	138	138	138	116
TM Est. Life	[hr]	16,000	16,000	16,000	3,000
Imp. Mass	[kg]	8,820	1,325	9,610	-
Imp. Emb. Energy	[MJ/kg]	129	129	133	-
Imp. Est. Life	[hr]	1,200	1,500	1,500	-

Table 4.7.
Conventional Agricultural Operation Results - Energy Consumption

Operation	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
Fertilize	218	134	7,800	0.3	8,153
Herbicide	27	17	48	0.2	92
Planting	202	200	1,722	0.5	2,125
Harvest	559	211	-	0.5	770

Table 4.8.
Conventional Agricultural Operation Results - Cost

Operation	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Fertilize	3.62	7.74	78.00	1.92	91.28
Herbicide	0.48	5.33	9.24	1.68	16.72
Planting	3.43	21.46	281.45	3.15	309.50
Harvest	9.25	33.93	-	3.55	46.73

4.2.2 Autonomous Configuration 1: Larger Machines

The first AAV configuration to be considered is one with larger machines similar to those used in Section 4.2.1. While these machines are not yet available on the market, an example can be seen in Figure 4.1. This Case IH autonomous concept vehicle is able to navigate fields automatically and is powerful enough to complete demanding tasks such as primary tillage operations.

Because AAVs do not need to accommodate a human operator, their design can be altered. For example, the concept vehicle shown in Figure 4.1 does not have

Figure 4.1. Case IH Autonomous Concept Tractor (Case IH, 2017)

a cab, thus reducing the weight of the machine and eliminating the need for air conditioning, control linkages, display units, and user controls. This weight reduction would decrease the power requirement of the machine and decrease the amount of energy consumed for propulsion. The removal of air conditioning would also save energy. Ružić and Časnji (2011) analyzed tractors with power ranges from 55-118 kW and concluded that the air conditioning unit consumes 2-6 kW.

The omitted components would also help to lower the cost of the machine because fewer raw materials would be required. On the other hand, autonomy has additional effects on the machine, such as increased cost from extra sensors and increased electrical consumption. Reported energy consumption of on-highway vehicle automation systems ranges from 200 W for SAE Level 2 automation (Baxter et al., 2018) to 1-3 kW for SAE Level 4 and 5 autonomous driving systems (Gawron et al., 2018; Hawkins, 2017). If it is assumed that similar components are used in agricultural vehicles that achieve supervised or full autonomy (see Section 2.3 and Figure 2.6), this additional electrical load effectively cancels out the energy savings realized from eliminating the traction machine's cab.

Furthermore, the total machine cost would presumably increase because it would be marketed as a premium product. The amount of price increase is hard to determine exactly, but a 10% premium seems reasonable based on automotive consumer studies (Larson et al., 2014).

Following the farming operations outlined in Section 4.1, UAN28% is applied post-harvest with a modified autonomous 187 kW (250 hp) tractor traveling 10.5 km/hr (6.5 mi/hr) with a field efficiency of 65% (e.g., John Deere 8295R T3 pulling a FAST 8300 liquid fertilizer applicator). Based on interviews and analyzing donated machinery, the estimated weight savings due to the traction machine modifications is about 10% of the overall traction machine weight; this 10% weight reduction is assumed for all traction machines in this AAV configuration. Because of the machine intelligence, the amount of fertilizer applied to the field can be more closely customized in order to apply only the amounts necessary. A recent study highlights the overuse of nitrogen fertilizer in the U.S. Midwest and uses non-commercial widely available satellite remote sensing to estimate the amount of nitrogen uptake in corn fields. The authors estimate that nitrogen fertilizer application could be reduced by half without significantly affecting crop yields (Basso et al., 2019). Reducing the amount of applied fertilizer not only lowers costs but also helps eliminate environmental damages. Based on this assumption, the application rate for UAN28% would be 140 L/ha (15 gal/acre), which equates to r_{fert} set at 50 kg N/ha (44.5 lb N/acre).

Along with fertilizer reduction, the application of pesticide would decrease due to the increased intelligence and automation of an autonomous self-propelled sprayer. As discussed in Section 2.4.4, AAVs have the ability to positively identify weeds and intelligently apply the appropriate amount of solution in the most effective locations. It is estimated that the amount of pesticide can be reduced by 65-95%, depending on the complexity of the system (Gonzalez-de Santos et al., 2017; Bechar and Vigneault, 2016; Gonzalez-de Soto et al., 2016). Based on a conservative assumption of a 65% decrease in 2,4-D use, the pre-plant burndown and the post-emergence application rate of 2,4-D is set at 0.20 kg ai/ha (0.18 lb ai/acre). The traction machine is a modified autonomous 55 kW (74 hp) tractor pulling a 12.2 m (40 ft) boom sprayer traveling 11.2 km/hr (7 mi/hr) with a field efficiency of 65% (e.g. John Deere 5085E pulling a FAST Big Wheel sprayer).

For the no-till planting operation, the traction machine is a modified autonomous 187 kW (250 hp) tractor pulling a 12 row planter traveling 8 km/hr (5 mi/hr) with a field efficiency of 65% (e.g., John Deere 8295R T3 with a John Deere 1775 12 row planter). The average population rate is 82,780 seeds/ha (33,500 seeds/acre). Finally, an autonomous 240 kW (320 hp) combine harvester with a 12 row corn head traveling 6.6 km/hr (4 mi/hr) with a field capacity of 70% (e.g. Gleaner S96). For each operation there is only one machine (i.e., the machines are not operating in a swarm), and there is one supervising worker for each machine.

A summary of the input parameters for Autonomous Configuration 1 is shown in Table 4.9. Output results in terms of energy consumption (MJ/ha) and cost ($/ha) are shown in Tables 4.10 and 4.11. Appendix A.2 contains all input values used for this analysis.

Table 4.9.
Autonomous Agricultural Operation Configuration 1 Inputs

Name	**Units**	**Fertilize**	**Herbicide**	**Planting**	**Harvest**
Operating Speed	[km/hr]	10.5	11.3	8	6.6
Field Eff.	[%]	65	65	65	70
Rated Width	[m]	11.4	12.2	9.1	9.1
TM Drive	[-]	MFWD	MFWD	MFWD	2WD
TM Throttle	[%]	80	75	80	100
TM Rated Power	[kW]	187	54	187	240
TM Mass	[kg]	10,510	4,205	10,510	21,520
TM Emb. Energy	[MJ/kg]	138	129	138	116
TM Est. Life	[hr]	16,000	16,000	16,000	3,000
Imp. Mass	[kg]	8,820	1,325	9,610	-
Imp. Emb. Energy	[MJ/kg]	129	129	133	-
Imp. Est. Life	[hr]	1,200	1,500	1,500	-

Table 4.10.
Autonomous Agricultural Operation Configuration 1 Results - Energy Consumption

Operation	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
Fertilize	214	133	3,900	0.3	4,247
Herbicide	27	17	17	0.1	61
Planting	198	198	1,722	0.3	2,118
Harvest	550	197	-	0.3	747

Table 4.11.
Autonomous Agricultural Operation Configuration 1 Results - Cost

Operation	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Fertilize	3.56	7.99	39.00	1.92	52.47
Herbicide	0.48	5.36	3.30	1.08	10.22
Planting	3.35	21.86	281.45	1.80	308.46
Harvest	9.11	37.32	-	1.80	48.23

4.2.3 Autonomous Configuration 2: Smaller Machines

The next configuration to be considered is one with smaller autonomous tractors (30-60 kW) operating in small groups. Initial analysis will only focus on a single machine working alone. In later sections the effects of operating in a swarm will be considered. The fertilizing operation utilizes a modified autonomous 55 kW (74 hp) tractor pulling a 5-knife liquid nitrogen applicator. The UAN28% application rate is 50 kg N/ha (44.5 lb N/acre).

For pesticide application, a 3-point mounted liquid sprayer is used instead of a self-propelled sprayer. The traction machine is a modified autonomous 55 kW (74 hp) tractor with a 7.6 m (25 ft) mounted sprayer. The 2,4-D application rate is 0.20 kg ai/ha (0.18 lb ai/acre).

Corn is planted using the same modified autonomous 55 kW (74 hp) tractor pulling a four row planter. The average population rate is 82,780 seeds/ha (33,500 seeds/acre). For the harvesting operation, a modified autonomous 205 kW (275 hp) combine harvesting with a four row corn head (e.g., Almaco R2). For each operation there is only one machine (i.e., the machines are not operating in a swarm), and there is one supervising worker for each machine.

A summary of the input parameters for Autonomous Configuration 2 is shown in Table 4.12. Output results in terms of energy consumption (MJ/ha) and cost ($/ha) are shown in Tables 4.13 and 4.14. Appendix A.3 contains all input values used for this analysis.

Table 4.12.
Autonomous Agricultural Operation Configuration 2 Inputs

Name	**Units**	**Fertilize**	**Herbicide**	**Planting**	**Harvest**
Operating Speed	[km/hr]	10.5	11.3	8	6.6
Field Eff.	[%]	65	65	65	70
Rated Width	[m]	3.81	7.62	3.05	3.05
TM Drive	[-]	MFWD	MFWD	MFWD	2WD
TM Throttle	[%]	75	75	50	95
TM Rated Power	[kW]	54	54	54	205
TM Mass	[kg]	2,880	2,880	2,880	15,830
TM Emb. Energy	[MJ/kg]	138	138	138	116
TM Est. Life	[hr]	16,000	16,000	16,000	3,000
Imp. Mass	[kg]	4,333	1,325	1,200	-
Imp. Emb. Energy	[MJ/kg]	129	129	133	-
Imp. Est. Life	[h]r	1,200	1,500	1,500	-

Table 4.13.
Autonomous Agricultural Operation Configuration 2 Results - Energy Consumption

Operation	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
Fertilize	205	189	3900	0.8	4295
Herbicide	44	27	17	0.4	88
Planting	138	83	1722	1.4	1944
Harvest	1119	435	-	1.6	1556

Table 4.14.
Autonomous Agricultural Operation Configuration 2 Results - Cost

Operation	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Fertilize	3.43	9.25	39.00	5.77	57.45
Herbicide	0.76	1.55	3.30	2.69	8.30
Planting	2.42	12.05	281.45	9.46	305.38
Harvest	18.65	82.85	-	10.65	112.15

4.2.4 Whole Farm Operation Study Results

A summary of the whole farm operation results can be seen below in Tables 4.15 and 4.16 and in Figures 4.2 and 4.3. In this present case study only focusing on whole farm operations, the instance with the lowest energy consumption and cost is when all autonomous large machines are used. From an energy stand point, the biggest savings comes from decreasing the amount of post-harvest fertilizer from 7,800 MJ/ha to 3,900 MJ/ha, as shown in Figure 4.2(c). Additional savings is seen in reduced pesticide use, but since the total amount of 2,4-D applied to the field is so low, it does not make much of an impact to the overall energy and cost consumption. Additionally, even though the total energy of the AAV Configuration 1 is 36% less than the conventional configuration, its cost is only 11% less. The main driver for cost is the planting material. At over 280 $/ha, the cost of corn seed outweighs all other costs and diminishes the effects of the other operations.

Finally, it is worth discussing the poor performance of AAV Configuration 2. This initial analysis only focused on a single machine working alone. In later sections the effects of operating in a swarm will be considered. When using smaller AAV machines working alone, their smaller engines results in lower fuel consumption; however, their narrower widths result in much lower field capacities (2.8 to 4.0 times smaller). The main reason why AAV Configuration 2 performed poorly is because of the smaller

Table 4.15.
Whole Farm Operation Results - Energy Consumption

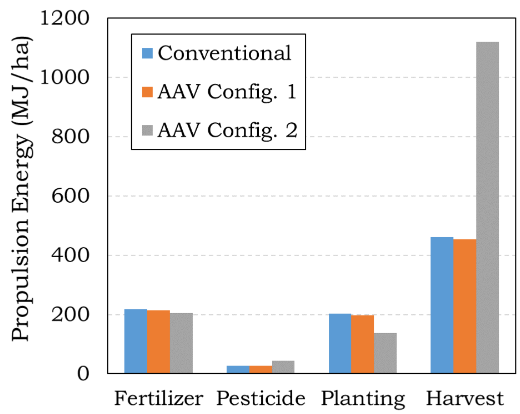
Operation	**Energy Consumption (MJ/ha)**				
	Propulsion	**Embodied**		**Labor**	**Total**
		Machinery	**Material**		
Conventional	1,034	579	9,617	1.8	11,232
AAV Config. 1	1,017	562	5,656	1.0	7,236
AAV Config. 2	1,549	760	5,656	4.6	7,968

Table 4.16.
Whole Farm Operation Results - Cost

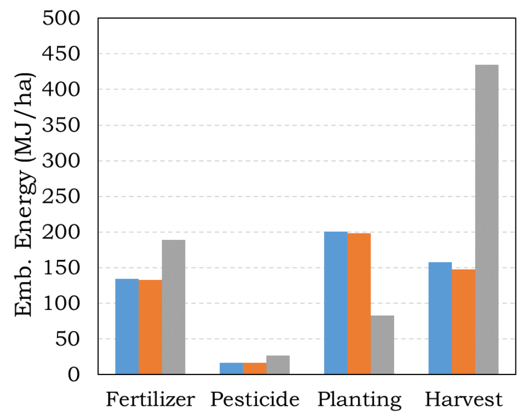
Operation	**Cost ($/ha)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Conventional	17.25	73.79	377.93	11.99	480.96
AAV Config. 1	16.97	77.89	327.05	6.96	428.87
AAV Config. 2	26.02	107.25	327.05	31.26	491.58

combine harvester. At only four rows wide, the Almaco R2 combine is 1/3 the width of a conventional 12 row combine; yet, it still has a 205 kW (275 hp) rated engine and weighs 14,061 kg (31,000 lb) compared to a 240 kW (320 hp) rated engine of a conventional large 12 row combine that weighs 18,048 kg (39,790 lb). This leads to high propulsion energy cost and labor costs, see Figures 4.2(a), 4.2(d), 4.3(a), and 4.3(d). With the additional time spent in the field, this leads to high machinery costs, see Figures 4.2(b) and 4.3(b). For the above analysis, the small combine price is set at $350,000. This price was chosen predicting high volume pricing for smaller combines and along with their smaller size/weight. In actuality, these small combine harvesters are mainly used in research activities and cost $800,000 and up.

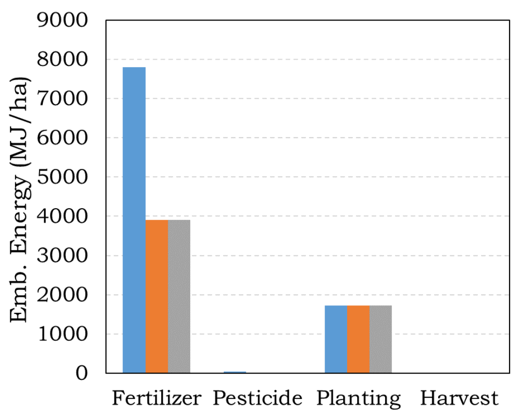
AAV Configuration 2 highlights the need to analyze each operation on an individual basis. Because of the poor performance of the small combine harvester, the entire



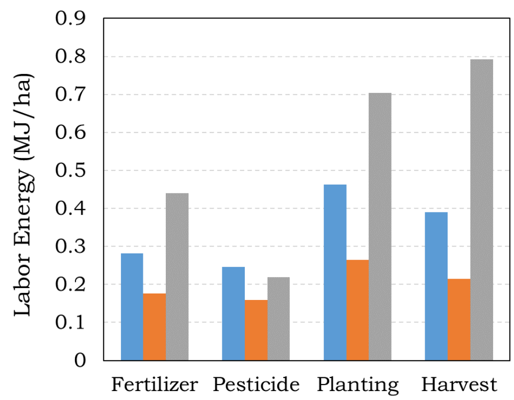
(a) Propulsion Energy



(b) Machinery Embodied Energy



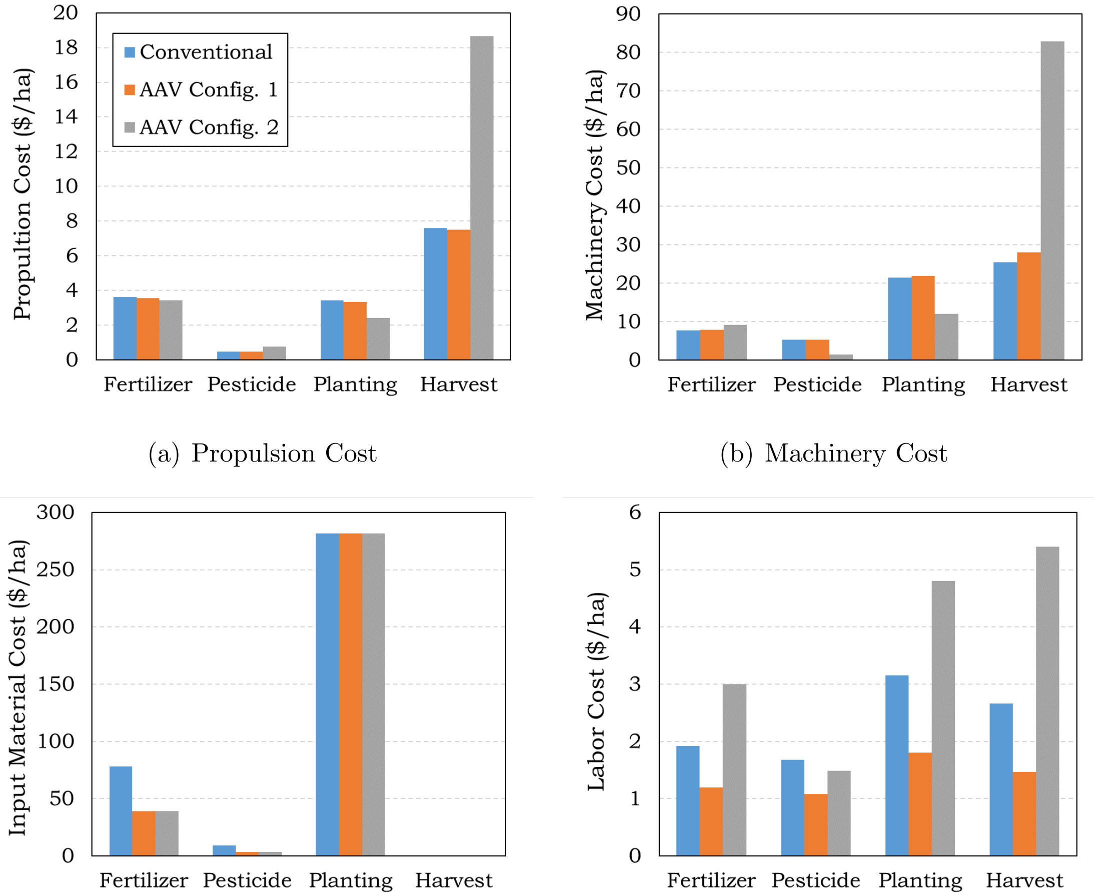
(c) Input Material Embodied Energy



(d) Labor Energy

Figure 4.2. Whole farm operation energy consumption rate

AAV Configure 2 would be disregarded as less efficient and more costly. However, if the small four row autonomous combine harvester is replaced with an autonomous 12 row harvester, the total energy consumption drops from 7,968 MJ/ha to 7,183 MJ/ha and the cost drops from 491.58 \$/ha to 416.32 \$/ha. In the next section, each task will be analyzed on an individual basis in order to give a better understanding of the most efficient and effective use of AAVs.



(a) Propulsion Cost

(b) Machinery Cost

(c) Input Material Cost

(d) Labor Cost

Figure 4.3. Whole farm operation cost consumption rate

4.3 Individual Task Operation Study

The previous sections analyzed and compared conventional and single-machine autonomous operations. In general, the propulsion energy/cost and the machinery embodied energy/cost were roughly the same between three categories (single large conventional, single large AAV, single smaller AAV). Major differences were seen in the decreased use of fertilizer (50% reduction), pesticide (65% reduction), and the increased labor cost of the single smaller AAV.

One potential advantage of using AAVs is their ability to work together in groups or swarms of other vehicles to complete an in-field operation. The energy consumption

(MJ/ha) and cost ($/ha) for propulsion, machinery, and input material is not effected by the inclusion of additional machines to a swarm; on a per-hectare-basis, the amount of fuel or embodied energy consumed will still be the same. For example, if there are twice as many machines, each machine will only be operating for half the amount of time. On the other hand, other factors are influenced when operating AAVs in a group instead of alone, such as the labor cost and operation time. While labor energy consumption (MJ/ha) is very small compared to the other three main energy sources, its cost ($/ha) is comparable to the propulsion cost.

In order to have a better perspective on the effects of using AAVs, it is helpful to introduce other performance metrics: task completion time and total costs. The total task completion time is the number of working days required to finish an in-field operation and is a function of machine speed, width, field efficiency, number of machines, and length of work day. Based on farmer interviews, a common in-field work day can range from 10-14 hours and can increase to 16-18 hours when timing becomes critical (e.g., needing to finish an operation before inclement weather). Examples of limiting factors to the length of work day include operator fatigue and poor visibility. Fully autonomous vehicles are able to operate 24 hours a day which can greatly decrease the number of working days required to finish an operation.

The total costs of an operation relevant to this analysis are shown below.

- Total machinery capital cost
    - Initial purchase price of machinery
    - $(p_{TM} + p_{imp})n_{machines}$
- Total labor cost
    - Total labor cost for operation
    - $C_{labor}a$

Each additional AAV that is added to a swarm will increase the overall initial capital cost of machinery, but it will decrease the amount of time required to complete an in-field operation.

In the following sections, the four crop production operations (fertilizing, spraying, planting, and harvesting) will be analyzed on an individual basis, with particular emphasis on the effect of AAVs operating in groups.

4.3.1 Fertilizing

For the example case scenario (Midwest U.S. corn production, 300 ha), liquid nitrogen fertilizer is applied below the soil surface using a drawn implement. Because of the high draft requirements of this type of fertilizer application, this present analysis is limited to the large tractors (187 kW John Deere 8295R T3 pulling a FAST 8300 liquid fertilizer applicator) and small tractors (54 kW John Deere 5085E pulling a 5-knife liquid fertilizer applicator) introduced in Section 4.2. By increasing the number of smaller autonomous tractors, more ground can be covered at once which decreases the labor cost and the number of working days for each operation.

As mentioned in the previous section, the energy consumption (MJ/ha) and cost ($/ha) for propulsion, machinery, and input material is not effected by the inclusion of additional machines to a swarm. These results are shown below in Tables 4.17 and 4.18. Labor energy consumption (MJ/ha) is very small compared to the other three main inputs, that it has been omitted. Labor cost ($/ha) is shown in Figure 4.4.

Table 4.17.
Fertilizing Results - Energy Consumption

Operation	**Energy Consumption (MJ/ha)**			
	Propulsion	**Embodied**		**Total**[(a)]
		Machinery	**Material**	
Conventional	218	134	7,800	8,152
Large Tractor AAV	214	133	3,900	4,247
Small Tractor AAV	205	189	3,900	4,294
[(a)] Labor energy consumption omitted				

Table 4.18.
Fertilizing Results - Cost

Operation	**Cost ($/ha)**			
	Propulsion	**Machinery**	**Material**	**Total**[(a)]
Conventional	3.62	7.74	78.00	89.36
Large Tractor AAV	3.56	7.99	39.00	50.55
Small Tractor AAV	3.43	9.25	39.00	48.25
[(a)]Not including labor cost, see Figure 4.4				

A comparison of the labor cost is shown in Figure 4.4. As the fertilizing operation transitions from large machines to small machines, the labor cost increases; the amount of time required to complete a task with a single small machine is much higher because of the narrower implement (15 row vs. 5 row). As more small AAVs are added to the swarm, the labor costs decreases. Even though the small tractor AAV implement width is narrower than the conventional machinery, the labor cost breaks even after two AAVs, with diminishing returns as more machines are added.

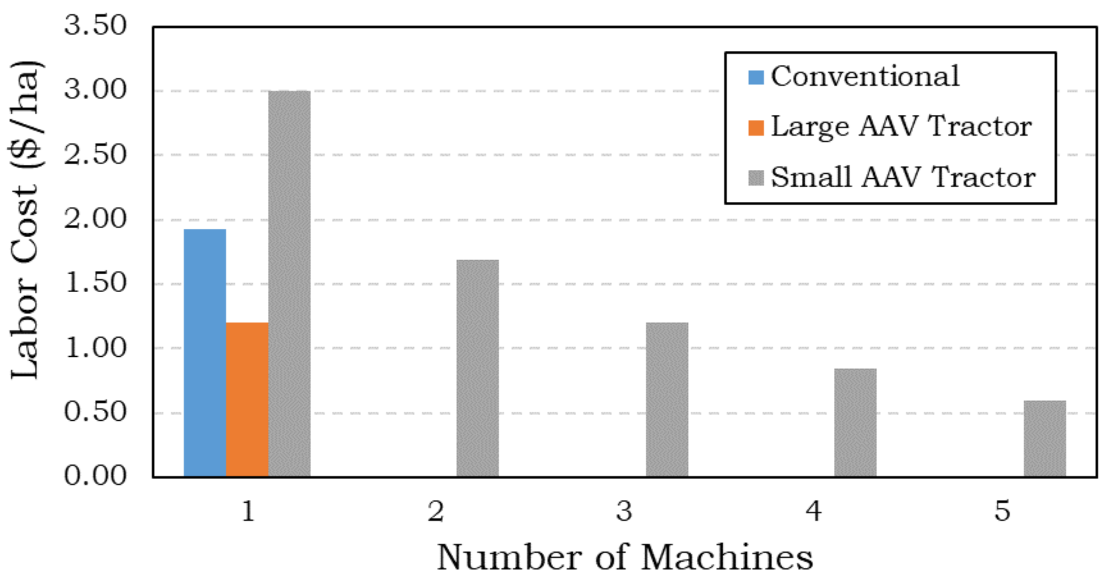


Figure 4.4. Fertilizing labor cost comparison

Figure 4.5 shows the total machinery capital cost for each configuration. Conventional agricultural operations commonly utilize large, expensive machinery. Small AAVs are an alternative approach, where smaller and less expensive machines are used. Each small AAV that is added to the swarm will increase the overall machinery capital cost. However, as seen in Figure 4.5, it takes more than four small AAVs in order to surpass the cost of a single large conventional machine. The prices chosen for this analysis are based on 2019 model year vehicles (see Appendices A.1–A.3).

Finally, Figure 4.6 shows the number of working days required to complete the fertilizing task. The conventional operation assumes a working day of 16 hr and the AAV operations assume a working day of 24 hr. For a conventional fertilizing operation, the total time is 38.5 hr, which equates to 2.4 working days. Because AAVs are able to work non-stop, it only requires two machines in order to complete the task in the same amount of time as a conventional large machine. As additional smaller AAVs are added to the swarm, the required work time continues to decrease. With four and five AAVs working simultaneously, the amount of working days can be decreased by more than half.

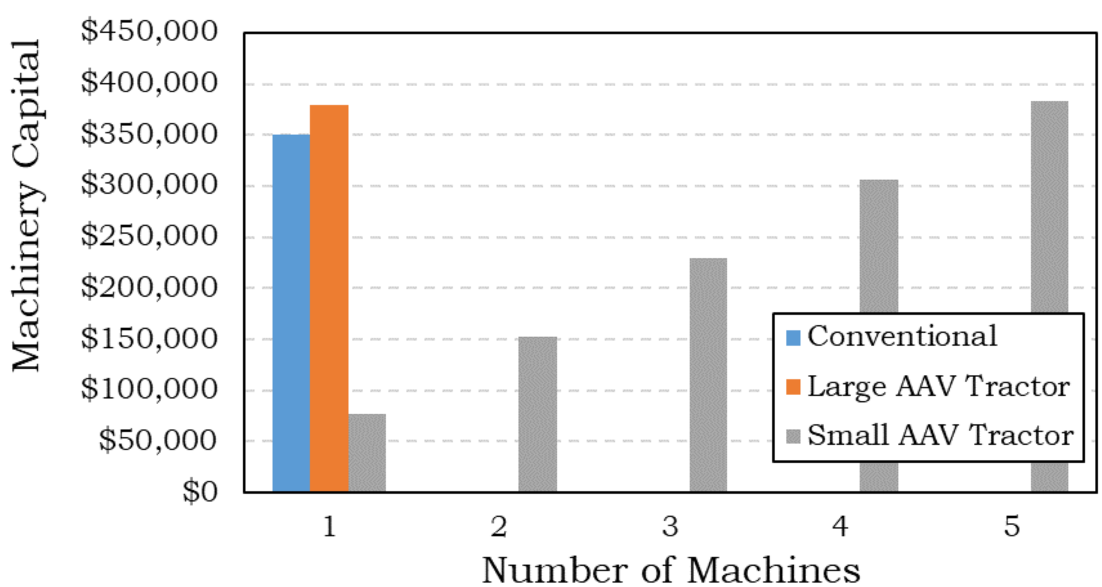


Figure 4.5. Fertilizing machinery capital cost comparison

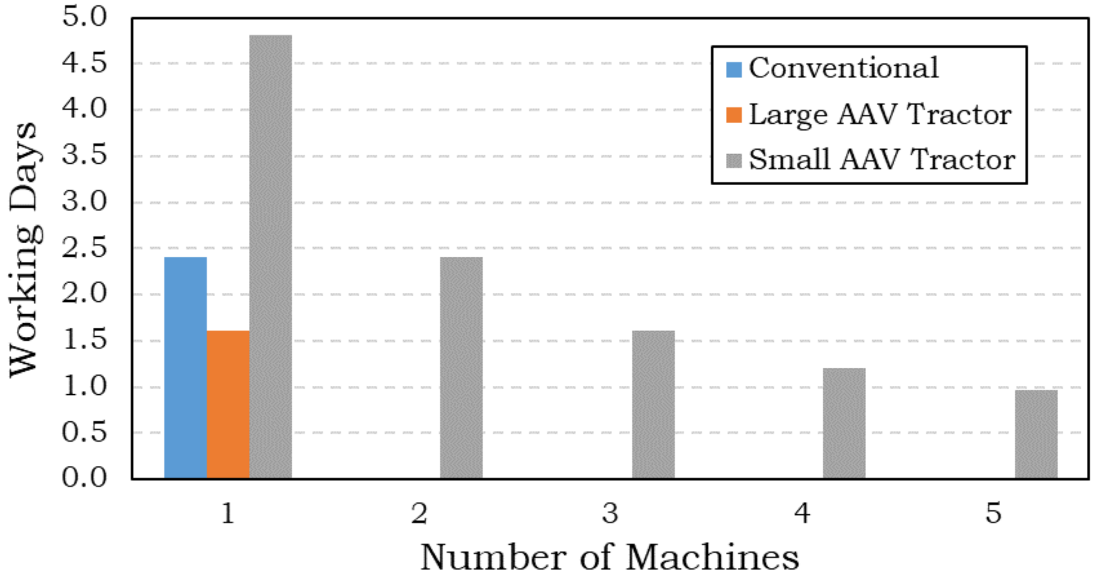


Figure 4.6. Fertilizing working days comparison

4.3.2 Spraying

The herbicide spraying operation occurs twice during this predefined crop production scenario: pre-plant and post-emergence. In the whole farm operation study (Section 4.2), a 55 kW (74 hp) tractor pulling a 12.2 m (40 ft) boom sprayer traveling at 11.3 km/hr (7 mi/hr) was used for the conventional operation and the larger AAV configuration. The smaller AAV configuration used the same tractor but a smaller 7.6 m (25 ft) mounted sprayer boom.

Two other AAV configurations for a spraying operation include a small utility vehicle (e.g., John Deere Gator) and a single-row machine. The small utility vehicle is based on research from Ball et al. (2015) where a modified autonomous electric John Deere TE Gator was equipped with a 5.5 m (18 ft) sprayer boom (Figure 4.7). This experimental machine was tested on a single 55 ha (136 acre) field with 12 simulated robots all working in coordination with each other. The single-row machine is based on an AAV from a startup company called Rowbot Systems. The vehicle is an articulated four wheeled machine that uses LiDAR and GPS to navigate between 30 inch rows (Figure 2.10).

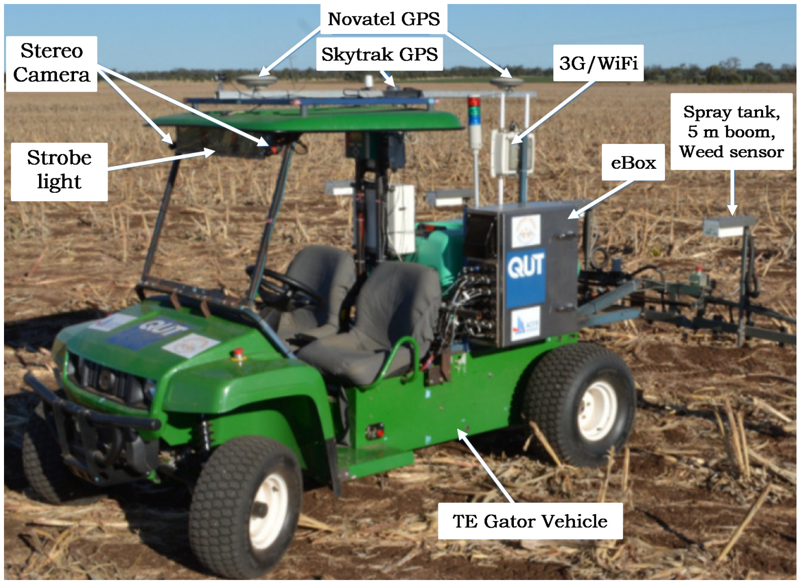


Figure 4.7. Autonomous electric John Deere TE Gator (Ball et al., 2015)

A summary of the input parameters for the utility AAV and the single-row AAV are shown in Table 4.19. Appendices A.4 and A.5 contain all input values used for this analysis. Tables 4.20 and 4.21 show the propulsion, machinery, and input material energy consumption and cost.

A comparison of the labor cost is shown in Figure 4.8. As the spraying operation transitions from larger machines to the utility and single-row machines, the labor cost is considerably higher because the those two AAVs are much more narrow than the larger machines. In general, labor costs are low for the conventional, large tractor AAV, and small tractor AAV operations because of the wider machines can travel quickly through the field; at 12.2 m wide traveling at 11.2 km/hr, the field capacity is 8.9 ha/hr and total in-field operation time of 33.6 hr. Similar to the fertilizing operation, as more small AAVs are added to a swarm, the labor costs decrease. For small tractor AAVs (54 kW John Deere 5085E), the labor cost outperforms the large tractor AAV once two machines are in use. The labor costs of utility AAVs match the conventional operation once 3 machines are in use, and it takes 12 single-row AAVs to achieve the same results.

Table 4.19.
Utility AAV and Single-row AAV Inputs for Spraying Operation

Name	Units	Utility AAV	Single-row AAV
Operating Speed	[km/hr]	5	6.4
Field Eff.	[%]	65	65
Rated Width	[m]	5.5	1.5
TM Drive	[-]	2WD	4WD
TM Throttle	[%]	100	50
TM Rated Power	[kW]	4.6	10
TM Mass	[kg]	900	544
TM Emb. Energy	[MJ/kg]	138	138
TM Est. Life	[hr]	3,000	3,000

Table 4.20.
Spraying Results - Energy Consumption

Operation	Energy Consumption (MJ/ha)			
	Propulsion	Embodied		Total[a]
		Machinery	Material	
Conventional	27	17	48	92
Large Tractor AAV	27	17	17	61
Small Tractor AAV	44	28	17	88
Utility Tractor AAV	6.0	23	17	46
Single-row AAV	48	39	17	104

[a]Labor energy consumption omitted

Figure 4.9 shows the total machinery capital cost for each configuration. The initial capital costs of a conventional machine and a large tractor AAV are \$118,000 and \$120,000, respectively. In order to match the initial cost of a conventional machine,

Table 4.21.
Spraying Results - Cost

Operation	Cost ($/ha)			
	Propulsion	**Machinery**	**Material**	**Total**[a]
Conventional	0.48	5.33	9.24	15.04
Large Tractor AAV	0.48	5.36	3.30	9.14
Small Tractor AAV	0.76	1.55	3.30	5.61
Utility Tractor AAV	0.22	2.95	3.30	6.47
Single-row AAV	1.01	5.23	3.30	9.54
[a]Not including labor cost, see Figure 4.8				

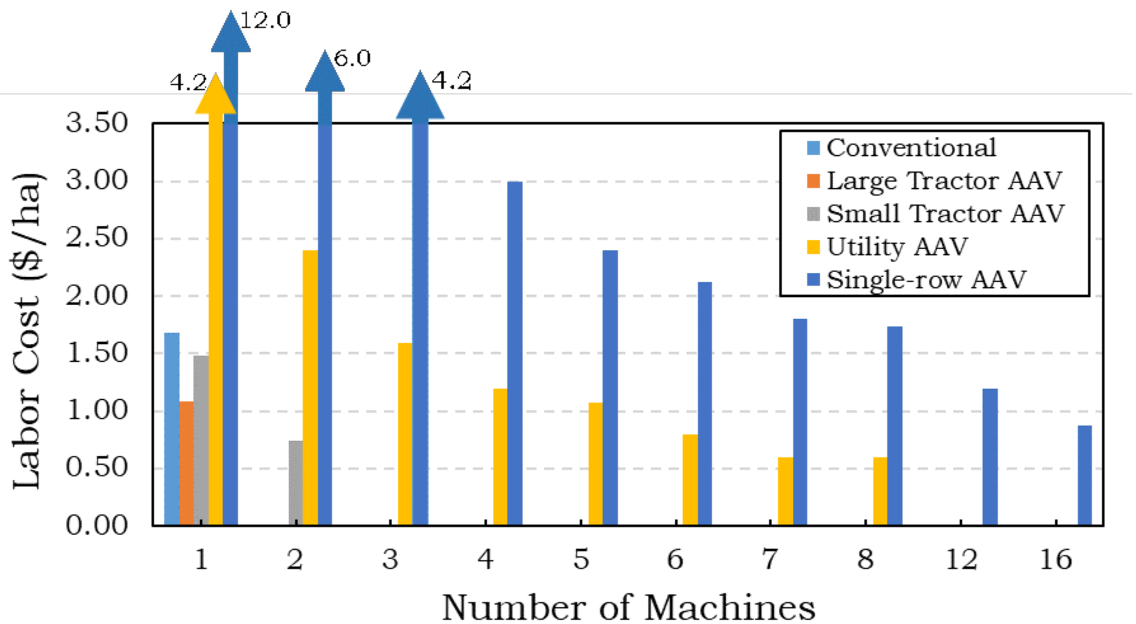


Figure 4.8. Spraying labor cost comparison

it would take more than two small tractor AAVs, more than seven utility AAVs, or 12 single-row AAVs.

Finally, Figure 4.10 shows the number of working days required to complete the spraying task. The conventional operation assumes a working day of 16 hr. The large

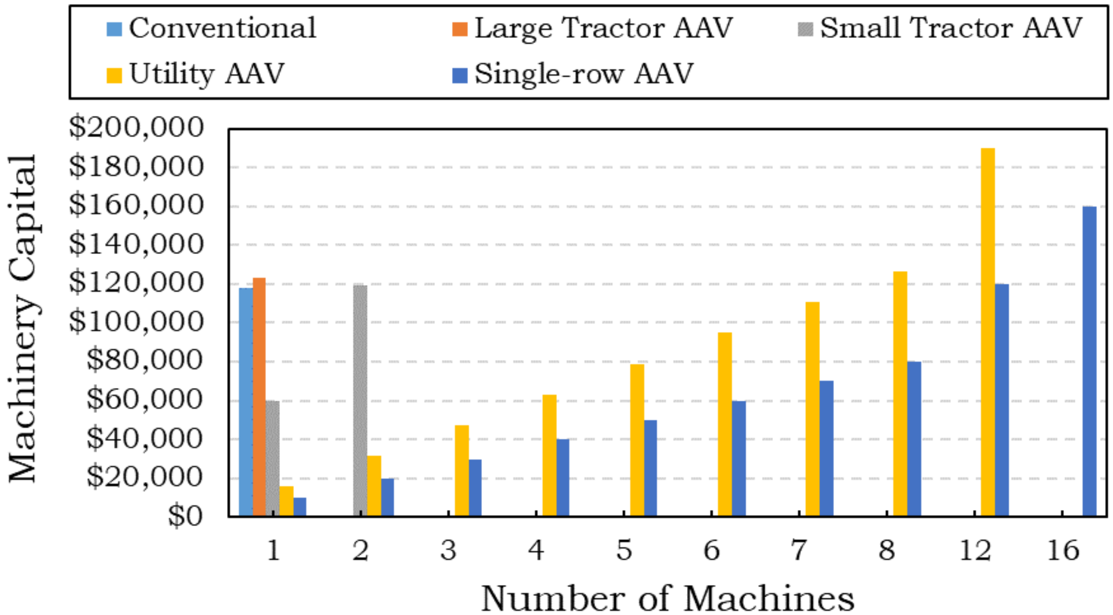


Figure 4.9. Spraying machinery capital cost comparison

tractor AAV, small tractor AAVs, and single-row AAVs all assume a working day of 24 hr because they are are powered by fossil fuel which allows for fast refueling. The utility AAV is an electric vehicle with a battery pack that allows for eight hours of continuous operation followed by a 12 hr recharge time. The total number of working days for the utility AAV is calculated using Equation 4.1.

$$t_{workDays} = \frac{(t_{elec,op} + t_{elec,charge}) \cdot INT\left[\frac{t_{field}}{t_{elec,op}}\right] + MOD\left[\frac{t_{field}}{t_{elec,op}}\right]}{24\,hr} \tag{4.1}$$

where $t_{elec,op}$ is the electric machine's continuous operation time (hr), $t_{elec,charge}$ is the electric machine's charge time (hr), and t_{field} is the total field task time (hr). With a total task time of 33.6 hr, the conventional spraying operation can be completed in just over two working days. To achieve this same total work day time, it requires two small tractor AAVs, seven utility AAVs, or 12 single-row AAVs.

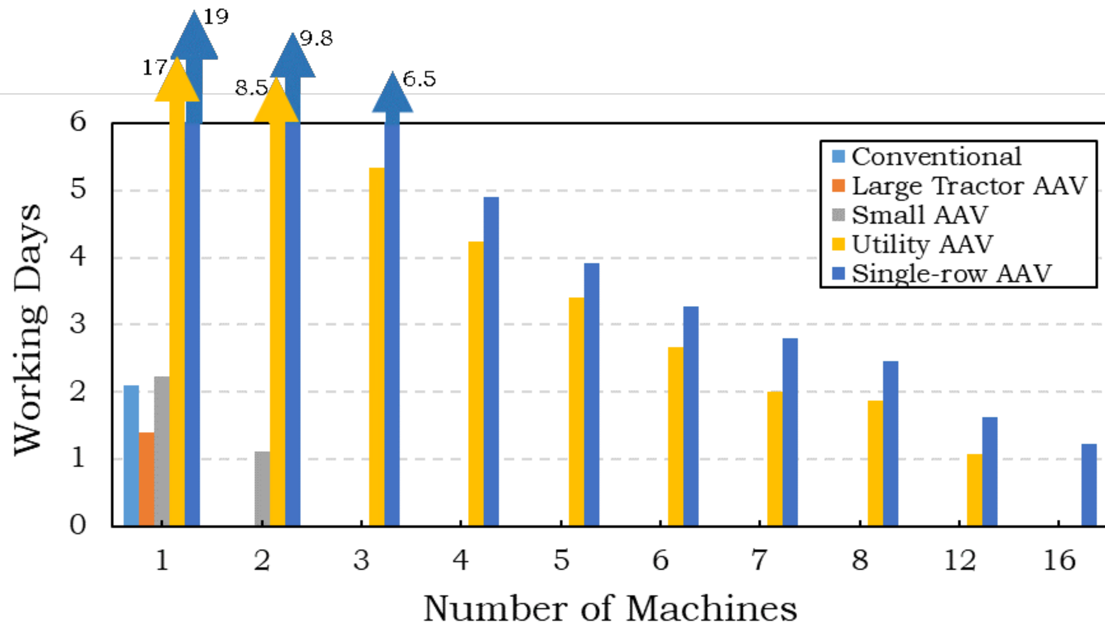


Figure 4.10. Spraying working days comparison

4.3.3 Planting

Corn is planted in 30 inch rows utilizing a no-till planting operation. The conventional operation is outlined above in Section 4.2.1 (187 kW traction machine pulling a 12 row planter traveling at 8 km/hr). The large tractor AAV operation uses the modified autonomous conventional machinery (see Section 4.2.2. The small AAV operation is outlined above in Section 4.2.3 (54 kW traction machine pulling a four row planter traveling at 8 km/hr).

Two other AAV configurations for the planting operation include a small utility tractor and a single-row machine. The small utility tractor is based on the University of Regina agBOT research vehicle that finished first place at the 2016 agBOT planting competition. This machine is an autonomous Kubota L2501DT pulling a two row Väderstad planter (Figure 4.11).

The single-row AAV is based on a concept machine from AGCO Fendt that is called Xaver (Figure 4.12). These small electric machines work together with a cloud-

Figure 4.11. The University of Regina agBOT seeder (Barker, 2016)

based system for precision corn planting. Each machine is powered by a 400 W electric motor and weighs about 65 kg. Its battery pack allows a single machine to cover 0.1 ha/hr and the machine can operate for 2.5 hr continuously. When the battery is low, a machine will automatically navigate back to the larger logistics unit for a 30 minute recharge (Fendt, 2017).

A summary of the input parameters for the utility AAV and the single-row AAV are shown in Table 4.22. Appendices A.6 and A.7 contain all the input values used for this analysis. Tables 4.23 and 4.24 show the propulsion, machinery, and input material energy consumption and cost.

Figure 4.12. Fendt Xaver single-row seeder (Fendt, 2017)

Table 4.22.
Utility AAV and Single-row AAV Inputs for Planting Operation

Name	**Units**	**Utility AAV**	**Single-row AAV**
Operating Speed	[km/hr]	8	2
Field Eff.	[%]	65	65
Rated Width	[m]	1.5	0.76
TM Drive	[-]	MFWD	4WD
TM Throttle	[%]	75	100
TM Rated Power	[kW]	18.1	0.4
TM Mass	[kg]	1,100	65
TM Emb. Energy	[MJ/kg]	138	138
TM Est. Life	[hr]	3,000	3,000

Table 4.23.
Planting Results - Energy Consumption

Operation	**Energy Consumption (MJ/ha)**			
	Propulsion	**Embodied**		**Total[a]**
		Machinery	**Material**	
Conventional	202	200	1,722	2,125
Large Tractor AAV	198	198	1,722	2,118
Small Tractor AAV	138	83	1,722	1,943
Utility Tractor AAV	167	96	1,722	1,985
Single-row AAV	35	30	1,722	1,787
[a]Labor energy consumption omitted				

Table 4.24.
Planting Results - Cost

Operation	**Cost ($/ha)**			
	Propulsion	**Machinery**	**Material**	**Total[a]**
Conventional	3.43	21.46	281.45	306.34
Large Tractor AAV	3.35	21.86	281.45	306.66
Small Tractor AAV	2.42	12.05	281.45	295.92
Utility Tractor AAV	2.93	11.45	281.45	295.83
Single-row AAV	1.28	22.99	281.45	305.72
[a]Not including labor cost, see Figure 4.13				

A comparison of the labor cost is shown in Figure 4.13. As the planting operation transitions from large machines to small machines, the labor cost is considerably higher because the small AAVs are much more narrow than the larger machines. As more small AAVs are grouped together, the labor costs decrease. For small tractor AAVs (54 kW John Deere 5085E), the labor cost breaks even when more than two tractors are used. The labor costs of utility AAVs match the conventional operation when more than four machines are in use, and it takes 26 single-row AAVs to achieve the same results.

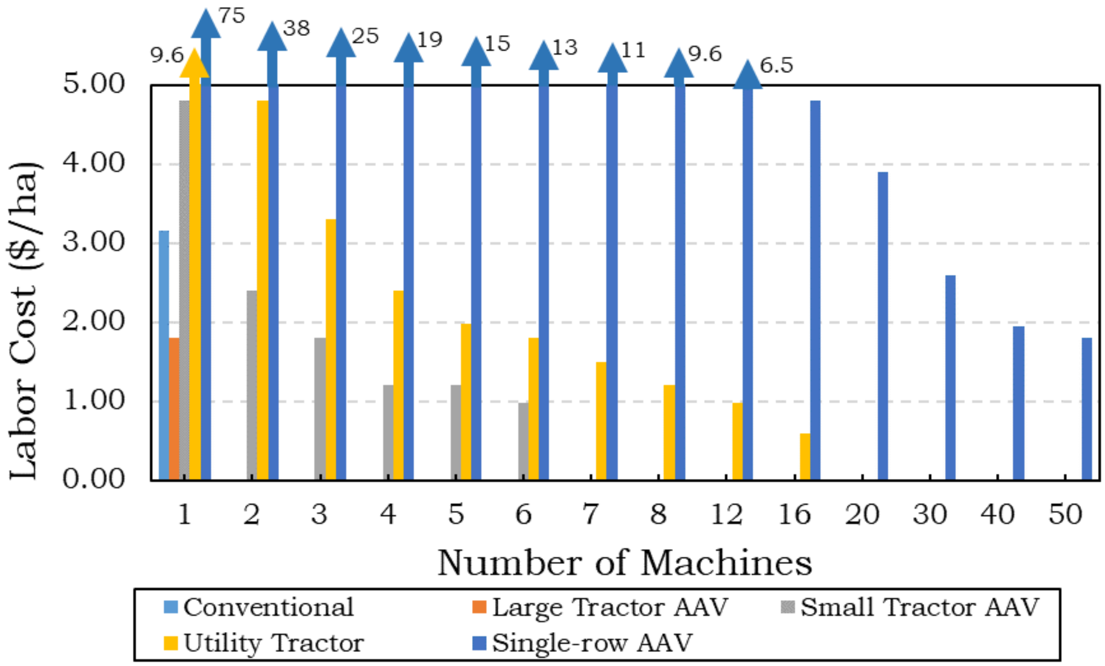


Figure 4.13. Planting labor cost comparison

Figure 4.14 shows the total machinery capital cost for each configuration. The initial capital costs of the conventional machinery and a the large tractor AAV machinery are $425,000 and $455,000, respectively. In order to match the initial cost of the conventional machinery, it would take more than six small AAVs, 16 utility AAVs, or 55 single-row AAVs.

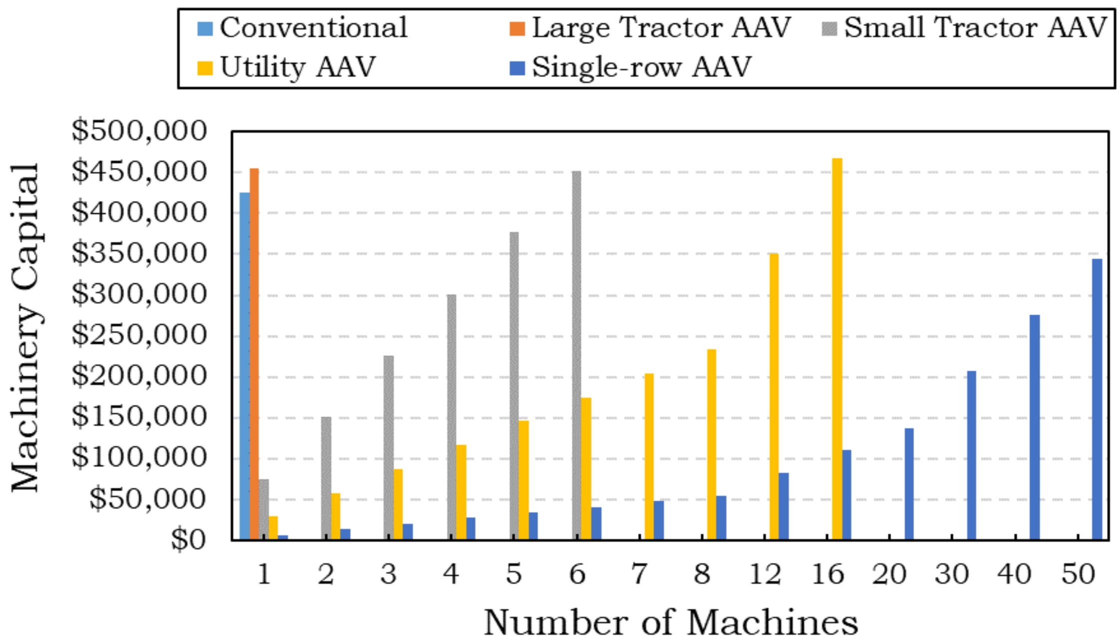


Figure 4.14. Planting machinery capital cost comparison

Finally, Figure 4.15 shows the number of working days required to complete the planting task. The conventional operation assumes a working day of 16 hr. The large tractor AAV, small tractor AAVs, and utility AAVs all assume a working day of 24 hr because they are powered by fossil fuel which allows for fast refueling. The single-row AAV is an electric machine with a battery pack that allows for 2.5 hr of continuous operation followed by 30 minute recharge time. The total number of working day for the single-row AAV is calculated using Equation 4.1.

With a total task time of over 63 hr, the conventional planting operation requires nearly four full working days. To achieve the same results, it requires two small tractor AAVs, four utility AAVs, or 39 single-row AAVs.

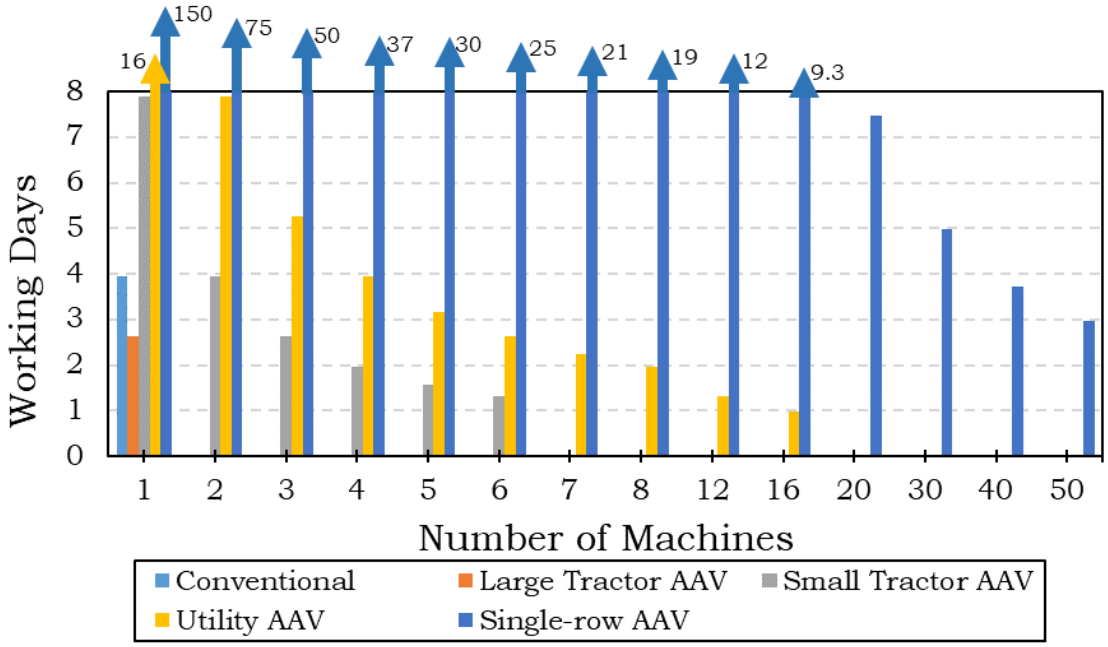


Figure 4.15. Planting working days comparison

4.3.4 Harvesting

The harvesting scenario only analyzes large and small combine harvesters. As discussed in Section 4.2.4, the smaller four row combine harvester has very poor performance compared to a conventional 12 row machine. Even though it is a smaller machine, it still requires high amounts of propulsion energy and cost due to its engine size, see Figures 4.2(a) and 4.3(a). Additionally, because the smaller combine harvester is only four rows wide, it would require at least two to three machines operating non-stop in order to match the performance of a large harvester. The capital costs of buying two to three smaller combines are enough to disregard this option compared to the conventional or autonomous large combine harvesters.

The energy and cost results from conventional harvesters and large AAV harvesters is shown below in Tables 4.25 and 4.26. The biggest advantage to using an autonomous harvester is the labor cost savings and the decreased amount of working days that are required to complete a task. The 300 ha harvesting task requires just over 71 hr to complete. This time equates to 4.4 working days for a conventional operation (16 hr work days). The autonomous large harvester is able to operate non-stop, which allows the task to be completed in 3.0 work days. This 24-hour operation is possible because corn can be harvested even at night. This is not the case for soybean harvest, where nighttime harvest is limited because the onset of dew at dusk does not allow for proper processing of the crop.

Table 4.25.
Harvesting Results - Energy Consumption

Operation	Energy Consumption (MJ/ha)				
	Propulsion	Embodied		Labor	Total
		Machinery	Material		
Conventional	559	210	-	0.5	770
Large Tractor AAV	550	197	-	0.3	747

Table 4.26.
Harvesting Results - Cost

Operation	Cost ($/ha)				
	Propulsion	Machinery	Material	Labor	Total
Conventional	9.25	33.93	-	3.55	46.73
Large Tractor AAV	9.11	37.32	-	1.80	48.23

4.3.5 Individual Task Operation Study Results and Conclusions

4.3.5.1 Fertilizing

The fertilizing operation looked at the outcome of using large conventional machinery, a large tractor AAV, and multiple small tractor AAVs. While the large tractor AAV has a higher machinery cost, it is able to work around the clock, which lowers the labor cost and allows the fertilizing operation to be completed in 1.6 working days (as opposed to 2.4 working days with conventional machinery). The energy and cost consumption for propulsion and machinery are nearly the same between the conventional machinery and the large tractor AAV. The amount of energy and cost associated with the input material is much lower with the AAVs because of the intelligent application of fertilizer, which decreases excess application.

Small tractor AAVs have a slightly lower propulsion cost because of their smaller engine and machine size. However, their machinery energy (MJ/ha) and costs ($/ha) are higher due to their lower field capacity. Since the small tractor AAVs can work together in a group, the labor costs and required working days can be decreased. It only takes two small tractor AAVs to meet or exceed the labor cost and working day performance of the conventional machinery. Yet, for the same amount of money as a conventional machine, four to five small tractor AAVs could be purchased. With a swarm of four AAVs, the labor cost drops to 0.84 $/ha (1.92 $/ha for conventional) and the operation can be completed in 1.2 working days (2.4 working days for conventional).

4.3.5.2 Spraying

The pesticide spraying operation introduced the utility AAV and the single-row AAV. For this 300 ha corn operation, pesticide is applied twice per season. The conventional machinery has a boom width of 12.2 m (40 ft) boom and travel speeds of 11.3 km/hr (7 mi/hr), it takes 33.6 hr to complete the task (labor cost 1.68 $/ha). The energy and cost consumption for propulsion and machinery are nearly the same between the conventional and large tractor AAV. The greatest benefit to utilizing AAVs is the intelligent application of pesticide, which can allow for 65–95% reduction in chemical use. Small tractor AAVs have very similar energy consumption and costs compared to large AAVs. In order to match the field capacity of the large machines, two small tractor AAVs are required. These two machines can complete the spraying task in 14.9 hr and cost roughly the same as a single conventional machine.

The utility AAV offers a unique advantage in that it is electrically powered. This greatly decreases the propulsion energy consumption and cost (6.0 MJ/ha, 0.22 \$/ha) compared to the conventional, large AAV, and small tractor AAVs (≈35 MJ/ha, ≈0.60 \$/ha). Because the utility AAV is so narrow, it requires at least 3 machines to match the labor cost of a conventional machine. Yet, it requires at least seven machines to meet or exceed the task time performance of 2.1 working days. This is because the battery pack of the utility AAV allows for eight hours of continuous operation, followed by a 12 hour recharge time.

Finally, the single-row machine is designed to navigate between rows of corn and apply pesticide where needed. Even through it is a low cost machine that is purpose built to work in swarms, it does not meet the performance of the other four machine types. Nine single-row AAVs need to be working together before the task time can decrease to 2.1 working days. While the pricing information is not available for this machine, \$10,000 seems to be a reasonable price. At that price these 12 machines could be purchased for the same price as the conventional machinery.

4.3.5.3 Planting

Corn is planted using a no-till planting operation. The conventional machinery is able to complete the planting task in 63.0 hr, which equates to nearly four 16 hr work days. As is the case with the other in-field operations, the propulsion and machinery energy consumption (MJ/ha) and cost (\$/ha) are nearly identical for the conventional machinery and the large tractor AAV. Because the planting rate (82,780 seeds/ha, 33,500 seeds/acre) is constant between all the different machine types, the input material energy consumption and costs do not change.

Where the conventional and large tractor AAV use a 12-row implement, the small tractor AAVs are only using a four-row implement. Yet, since the small tractor AAVs can operation around the clock, it only requires two machines in order to match the labor cost of the conventional machine (small tractor AAV: 2.40 \$/ha; conventional:

3.16 \$/ha). In order to complete the planting task as fast as conventional machinery, two small tractor AAVs are also required. This allows the working day time to decrease to 3.9 working days. These two small tractor AAVs could complete the task just as fast, yet their cost is nearly 60% less. Six small tractor AAVs can be purchased with the same amount of machinery capital cost as the conventional operation. This would decrease the labor cost to 0.98 \$/ha (compared to 3.16 \$/ha) and the operation could be completed in 1.3 working days (compared to 3.9 working days).

The utility AAV shows a similar trend. While the machine is much more narrow (two-row implement), it does not cost nearly as much as the conventional machinery. It requires four utility AAVs to match the labor cost of the conventional machine and to complete the planting task in the same amount of working days. At only ≈\$29,000 per AAV, six utility AAVs cost 68% less than the conventional machinery. Fourteen utility AAVs could be purchased with the same amount of machinery capital costs as the conventional operation. The labor cost would decrease to 0.75 \$/ha and the operation could be completed in 1.1 working days.

The single-row AAV is battery powered and allows for 2.5 hr of continuous operation, followed by a 30 minute recharge. To complete the planting task in less than four working days, 40 single-row AAVs are required. Yet only 39 single-row AAVs are needed to meet the labor cost. The machinery capital costs of 40 single-row AAVs are 38% lower than the conventional machinery costs, and 61 machines could be purchased for the same amount as the conventional machinery. If 61 single-row AAVs were utilized, the labor cost would decrease to 1.26 \$/ha and the operation could be completed in 2.44 working days.

4.3.5.4 Harvesting

As discussed in Section 4.3.4, only the conventional and large AAV are considered in this analysis. In general, the energy consumption and costs are relatively the same between the two machines. While the large AAV harvester will weigh less, its cost will be higher. The advantage of the autonomous harvester is that is can operate continuously, whereas the conventional machine is limited by operator fatigue or visibility. The small AAV harvester was omitted from the analysis because of its poor performance. Because of its narrower width, it would require three small AAV harvesters in order to meet the performance of one conventional machine. The machinery capital costs and propulsion costs make this option impractical.

4.4 Production Efficiency Metrics

4.4.1 Energy-per-unit-area

As seen in the case study analysis above, there are many factors at play when comparing the pros and cons between different vehicle configurations. The goal is to present the data in a way that allows for an objective comparison between the different agricultural operations. One metric that has been shown above is energy-per-unit-area. This is displayed as MJ/ha, but it could be altered for other units. This metric shows the amount of energy (direct or embodied/sequestered) that is consumed over the entire field, regardless of the task time required for the operation. The energy consumption (MJ/ha) for propulsion, machinery, and input material is independent of the number of the machines simultaneously in use; on a per-hectare-basis, the amount of fuel or embodied energy consumed will still be the same regardless of how many machines are operating at once. The labor energy consumption does change with the number of AAVs working together; however, the analysis above shows that the labor energy consumption can be ignored because it is insignificant compared to the other inputs (i.e., propulsion, machinery, and input material). Since labor energy consumption can be omitted, energy-per-unit-area is a helpful metric to determine energy consumption, regardless of how many machines are being used.

Looking only at energy-per-unit-area, there is little difference between conventional large machines and large AAVs. The difference is seen in the reduced propulsion needed, since large AAVs are lighter than their conventional counterparts. Additionally, AAVs are able to apply agrochemicals more efficiently and intelligently, and this reduces the amount of input material embodied energy consumption. As machine size decreases, sometimes it makes sense (from an energy standpoint) to use small tractor AAVs instead of large machines; this is the case for fertilizing and planting. However, during the spraying operation, a small tractor AAV consumes more propulsion energy than the large traction machines. Electric machines are by far the most efficient choice in terms of energy-per-unit-area. This is due to the high efficiencies of electric vehicles compared to fossil fuel machines. Some downsides of using electric machines include the higher cost-per-unit-energy and the requirement to recharge batteries.

4.4.2 Energy-per-field-time

Reporting energy-per-field-time is a helpful metric to show the effects of multiple AAVs working together. Once again, the results of the conventional operations are the benchmarks to which the other operations are compared to. This metric is calculated using Equation 4.2.

$$\dot{E} = E \cdot C_a \tag{4.2}$$

where E is energy consumption (MJ/ha) and C_a is field capacity (ha/hr). The resulting values are expressed in terms of MJ/hr. While this could be equated to power ($kW = \frac{MJ}{hr}\frac{1}{3.6}$), it is more intuitive to express $\dot{E}$ in terms of MJ/hr, since power is commonly associated with engines, torque/speed, etc. Example results are shown in Tables 4.27 and 4.28. Once again, the labor is neglected because the insignificant amount of energy that is consumed. While it is informative to know the energy consumption per hour, it does not always reveal the whole picture. For example, while Table 4.27 shows that two small tractor AAVs working together consume 37% less energy per hour than conventional machines, it does not reveal that the field time of two small AAVs is 58 hr compared to only 38 hr by the conventional operation.

Table 4.27.
Fertilizing Results - Energy-per-field-time

Operation	Energy Consumption (MJ/hr)			
	Propulsion	Embodied		Total[(a)]
		Machinery	Material	
Conventional	1,703	1,049	60,848	63,600
Large Tractor AAV	1,673	1,039	30,424	33,136
Small Tractor AAV[(b)]	1,065	981	30,424	32,470

[(a)]Labor energy consumption omitted

[(b)]Two AAVs used, matches conventional labor cost

Table 4.28.
Spraying Results - Energy-per-field-time

Operation	Energy Consumption (MJ/hr)			
	Propulsion	Embodied		Total[(a)]
		Machinery	Material	
Conventional	234	146	425	806
Large Tractor AAV	244	150	152	546
Small Tractor[(b)] AAV	243	150	95	489
Utility AAV[(c)]	32	124	91	247
Single-row AAV[(d)]	363	300	130	793

[(a)]Labor energy consumption omitted

[(b)]One AAV used, matches conventional labor cost

[(c)]Three AAVs used, matches conventional labor cost

[(d)]Twelve AAVs used, matches conventional labor cost

4.4.3 Cost-per-unit-area

Equations 3.28–3.32 calculate the cost in terms of \$/ha for each of the four main inputs (i.e., propulsion, machinery, input material, and labor). This performance metric shows the financial cost that is accrued for the entire field area, regardless of the task time required for the operation. The cost (\$/ha) for propulsion, machinery, and input material is independent of the number of machines working together. The labor cost does change with the number of AAVs working together; and contrary to the energy-per-unit-area metric, the labor costs are a meaningful portion of the overall costs.

There is little cost difference between conventional and large tractor AAVs, except for input material cost (because AAVs are able to apply agrochemicals intelligently). Large tractor AAVs have lower labor costs (1.20 \$/ha vs. 1.92 \$/ha) because they are able to operate around the clock and finish the task in less working days. Cost-per-unit-area gives helpful perspective on the implications of using multiple AAVs and electric machines. Labor cost is of similar magnitude to propulsion cost and is decreased as more AAVs work together. Discussion on the effects of AAVs and labor cost (\$/ha) can be seen above in Section 4.3

4.4.4 Cost-per-field-time

Just like energy-per-field time, cost-per-field-time is a helpful metric to show the effects of multiple AAVs working together. This metric is calculated using Equation

$$\dot{C} = C \cdot C_a \tag{4.3}$$

where C is the cost consumption (\$/ha) and C_a is field capacity (ha/hr). Example results are shown in Tables 4.29 and 4.29.

Table 4.29.
Fertilizing Results - Cost-per-field-time

Operation	**Cost ($/hr)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Conventional	28.26	60.42	608.48	15.00	712.15
Large Tractor AAV	27.77	62.29	304.24	9.36	403.66
Small Tractor AAV[a]	17.81	48.12	202.83	8.76	277.51
[a]Two AAVs used, matches conventional labor cost					

Table 4.30.
Spraying Results - Cost-per-field-time

Operation	**Cost ($/hr)**				
	Propulsion	**Machinery**	**Material**	**Labor**	**Total**
Conventional	4.09	47.59	82.49	15.00	149.14
Large Tractor AAV	4.24	47.89	29.46	9.64	91.23
Small Tractor AAV[a]	4.24	8.62	18.43	8.30	59.59
Utility AAV[b]	1.15	15.8	17.69	8.57	43.21
Single-row AAV[c]	7.73	40.00	25.25	9.18	82.16
[a]One AAVs used, matches conventional labor cost [b]Three AAVs used, matches conventional labor cost [c]Twelve AAVs used, matches conventional labor cost					

4.4.5 Working Days

Tracking the number of working days helps provide a better perspective on the amount of time required to complete a task. The number of working days required to finish a task is a function of machine speed, width, field efficiency, number of machines, and length of work day. For a given task, a conventional operation may require less field time but more working days because of the limits of human operators, such as operator fatigue or poor visibility. For the analysis in this chapter, the length of work day for conventional operations was set at 16 hr, based on farmer interviews (10–14 hr for a common in-field work day; 16–18 hr when timing is critical). AAVs have the advantage of working non-stop with a 24 hr work day. This could allow even a slower or more narrow machine to complete the task sooner than a conventional operation.

4.4.6 Machinery Capital Cost

Finally, machinery capital cost is an important metric to use when comparing conventional machines with AAVs. Conventional farming operations typically opt for large, wide machines that are able to quickly travel through a field and cover large swaths of ground in a short amount of time. As these machines increase in size and complexity, their costs also increase. Analyzing the overall machinery capital cost gives a helpful perspective on how effective these large machines are compared to AAVs. There were four classes of AAVs that were analyzed in the previous sections: large traction machine, small traction machine, utility, and single-row. With the three smaller classes of AAVs, multiple machines are needed in order to meet the performance of a single conventional machine. In nearly every instance, for the same amount of machinery capital cost, AAVs were able to exceed the performance of conventional machinery. While capital costs do not provide the entire financial picture, it is an effective starting point in helping compare AAVs to conventional machines.

5. MODELING TOOL

The final objective of this research is to develop a modeling tool that allows users to evaluate the use of AAVs in the crop production process. The modeling tool allows a user to interact with the energy model in a user-friendly environment and allows for parameter studies and what-if analysis to be performed.

5.1 Microsoft Excel Energy Model Workbook

The energy model and underlying equations were developed in Microsoft Excel. This software was chosen because it allows for easy distribution to and evaluation by a wide audience who may be deterred from using a more expensive software package. The energy model spreadsheet is contained within a single Microsoft Excel workbook that contains five sheets. The first sheet contains instructions about the workbook and a button that launches the modeling tool graphical user interface (GUI). The user may stop here and immediately begin to use the modeling tool GUI, or may proceed to next sheet.

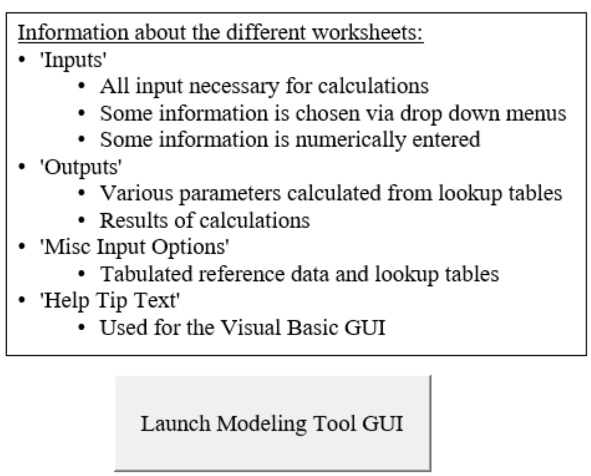


Figure 5.1. Microsoft Excel energy model *Instructions* sheet

The *Inputs* sheet is the next worksheet and displays all the necessary inputs for the energy model calculations. A partial view of the spreadsheet is shown in Figure 5.2; the entire spreadsheet is shown in Appendix B.1. The sheet is organized in a 6-column format which displays the parameter names, units, mathematical symbols, values, comments, and cited literature sources. Data can be directly added to the *Inputs* sheet or added via the GUI. Care has been taken to include ample information and clarification about each input; however, the GUI provides more description and helpful tips for entering correct values.

Multiple data sets can be added to the spreadsheet in order to analyze different operations. Figure 5.2 displays one data set with its name (*[Data Set Name]*) given in cell D3. Any additional data sets can be manually added by inserting additional columns between the **Symbol** column (column C) and the **Comment** column (column E). New data sets can also be added using the energy model GUI and are automatically inserted in the correct locations.

	A	B	C	D	E	F
1	Launch Modeling Tool GUI					
2						
3	**Name**	**Units**	**Symbol**	***[Data Set Name]***	**Comment**	**Source**
4	Machine Type	[--]	[--]	Conventional	Conventional, Autonomous, Autonomous Swarm	
5	No. of Machines	[--]	$n_{machines}$	1	Number of machines	
6	Machines per Operator	[--]	n_{MpO}	1	Number of machines per operator. 1 for conventional	
7	Soil/Ground Condition	[--]	[--]	Firm	Concrete, Firm, Tilled, Soft	[3] section 3.1 figure 1
8	Field Area	[ha]	a	300		
9	Operation Type	[--]	[--]	Miscellaneous		
10	Operation	[--]	[--]	Liquid Fertilizer Applicator		
11	Field Efficiency	[--]	E_f	0.65	How efficient at time in field. Recommended value:	[1] pg 5, [3] section 5
12						
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel	Fossil Fuel or Electric	
14	Traction Machine Drive Type	[--]	[--]	MFWD	2WD, MFWD, 4WD	[3] section 3.1 figure 1
15	Traction Machine Operating Speed	[km/h]	s	10.5	Speed of traction machine	Industry standards for ea

Figure 5.2. Microsoft Excel energy model *Inputs* sheet

While the input values are being added, the *Outputs* sheet performs calculations and displays the results. A partial view of the spreadsheet is shown in Figure 5.3; the entire spreadsheet is shown in Appendix B.2. The sheet is organized in the same 6-column format. The outputs for each data set are displayed between the **Symbol** column (column C) and the **Comment** column (column E). There is additional information shown above the data set values to give helpful reference information for the operation being evaluated (see cells D1, D2, and D3). If a new data set is manually added to the *Inputs* sheet, an extra column must also be added to the *Outputs* sheet and formulas from the previous data set output column must be copied to the newly inserted cells. When adding data sets via the energy model GUI, these operations takes place automatically.

The *Outputs* sheet displays all outputs from the energy model, even if some of them are irrelevant to the user. Towards the bottom of the sheet, the final output values are displayed (such as energy consumption, costs, and task completion time). Because this model is built within Microsoft Excel, it is trivial to add new outputs or calculations. Graphs can also be created within the workbook to help visualize the output of the energy model.

	A	B	C	D	E	F
1			**Machine Type:**	Conventional		
2	Launch Modeling Tool GUI		**No. of Machines:**	1		
3			**Operation:**	Liquid Fertilizer Applicator		
4						
5	**Name**	**Units**	**Symbol**	***[Data Set Name]***	**Comment**	**Source**
6	Tractive Efficiency	[--]	E_t	0.76	Tractive condition; depends on tractor drive type and soil/ground condition	[3] section 3.1 figure 1, [2] section 4.2
7	Rotary Power Parameter a	[kW]	a_{pto}	0	Machine specific parameter. For calculating rotary operation PTO power require	[3] Table 2, [2] section 4.1.2
8	Rotary Power Parameter b	[kW/m]	b_{pto}	0	Machine specific parameter. For calculating rotary operation PTO power require	[3] Table 2, [2] section 4.1.2
9	Rotary Power Parameter c	[kW·h/t]	c_{pto}	0	Machine specific parameter. For calculating rotary operation PTO power require	[3] Table 2, [2] section 4.1.2
10	Soil Parameter	[--]	F_i	0.96	Depends on implement soil texture type (i.e. F_1, F_2, F_3)	[3] Table 1, section 4.1.1
11	Machine Parameter A	[--]	A_{imp}	1800	Machine specific parameter. For calculating implement draft	[3] Table 1, section 4.1.1
12	Machine Parameter B	[--]	B_{imp}	0	Machine specific parameter. For calculating implement draft	[3] Table 1, section 4.1.1
13	Machine Parameter C	[--]	C_{imp}	0	Machine specific parameter. For calculating implement draft	[3] Table 1, section 4.1.1
14	Field Capacity	[ha/h]	C_a	7.80	Effective field capacity	[2] section 5.2
15	Total Field Task Time	[h]	t_{field}	38.5	Time it takes to complete the desired task	
16	Implement Soil and Crop Resistance	[N]	MR_{SC}	25920.0	Total force parallel to direction of travel that is required to propel the implement	[3] section 4.1.1, [2] section 4.1.1

Figure 5.3. Microsoft Excel energy model *Outputs* sheet

The last two sheets, *Misc Input Options* and *Help Tip Text*, are used to support the back end of the calculation spreadsheet and the energy model GUI. A partial view of the *Misc Input Options* spreadsheet is shown in Figure 5.4; the entire spreadsheet is shown in Appendix B.3. This sheet contains information for lookup tables that are needed for the calculations on the *Outputs* sheet. This format is helpful because it gives the opportunity to tweak values or add operations that may be missing from typical datasheets or standards.

The *Help Tip Text* spreadsheet is shown below and a full view is given in Appendix B.4. This spreadsheet contains text that is displayed in the energy model GUI that provides additional information or helpful tips on the a particular parameter. Any additional information that is added to these cells will automatically appear within the GUI, which is useful if additional clarity is necessary for a particular input variable.

Field Efficiency		
Tillage	Range	Typ.
Moldboard plow	0.7-0.9	85
Heavy-duty disk	0.7-0.9	85
Tandem disk harrow	0.7-0.9	80
(Coulter) chisel plow	0.7-0.9	85
Field cultivator	0.7-0.9	85
Spring tooth harrow	0.7-0.9	85
Roller-packer	0.7-0.9	85
Mulcher-packer	0.7-0.9	80
Rotary hoe	0.7-0.85	80
Row crop cultivator	0.7-0.9	80
Planting		
Rotary tiller	0.7-0.9	85
Row crop planter	0.5-0.75	65
Grain drill	0.55-0.8	70

Tractive Condition				
Type	Concrete	Firm	Tilled	Soft
2WD	87	72	67	55
MFWD	87	76	72	64
4WD	88	77	75	70
Track	88	76	74	72

Rotary Power Requirement Parameters			
	Parameter		
Machine Type	a	b	c
None	0	0	0
Baler, small rectangular	2	0	1.02
Baler, large rectangular bales	4	0	1.3
Baler, large round (var. chamber)	4	0	1.1
Baler, large round (fix. chamber)	2.5	0	1.8
Beet harvester	0	4.2	0

Implements							
		Machine Parameters			Soil Parameters		
	Width Units	A	B	C	F1	F2	F3
Major Tillage Tools					Fine	Medium	Coarse
Subsoiler/manure injector - narrow point	tools	226	0	1.8	1	0.7	0.45
Subsoiler/manure injector - 30 cm winged point	tools	294	0	2.4	1	0.7	0.45
Moldboard plow	m	652	0	5.1	1	0.7	0.45
Chisel plow - 5 cm straight point	tools	91	5.4	0	1	0.85	0.65
Chisel plow - 7.5 cm shovel/ 35 cm sweep	tools	107	6.3	0	1	0.85	0.65
Chisel plow - 10 cm twisted shovel	tools	123	7.3	0	1	0.85	0.65
Sweep plow - primary tillage	m	390	19	0	1	0.85	0.65
Sweep plow - secondary tillage	m	273	13.3	0	1	0.85	0.65
Disk, harrow, tandem - primary tillage	m	309	16	0	1	0.88	0.78
Disk, harrow, tandem - secondary tillage	m	216	11.2	0	1	0.88	0.78
Disk, harrow, offset - primary tillage	m	364	18.8	0	1	0.88	0.78
Disk, harrow, offset - secondary tillage	m	254	13.2	0	1	0.88	0.78

Figure 5.4. Microsoft Excel energy model *Misc Input Options* sheet

Operation Tab	Field Tab	Traction Machine Tab	Traction Machine Axles Tab
Machine Type: Conventional - typical machines, powered mostly by fossil fuels, directly operated by humans Autonomous - robotic machines operating without direct human intervention and control Autonomous Swarm - fleet of robotic machines operating in	Soil/Ground Condition: Common cone index (CI) values: - Hard/Concrete: > 1800 kPa - Firm: 1200 kPa - Tilled: 900 kPa - Soft: 450 kPa	Throttle Setting: Ratio of partial throttle engine speed to full throttle engine speed at operating load	Tire Section Height: Height of undeflected section. Equals [section width] × [aspect ratio]
Number of Machines: Number of machines operating in 'Autonomous	Field Efficiency: Measure of how efficient machine time is spent effectively operating	Mechanical Efficiency: Mechanical efficiency of the transmission and power train	Tire Overall Diameter: Undeflected overall tire diameter

Figure 5.5. Microsoft Excel energy model *Help Tip Text* sheet

5.2 Graphical User Interface

The energy model GUI is a custom-built application within the energy model spreadsheet that is created using Visual Basic for Applications (VBA). Because VBA is used, the file extension for the energy model spreadsheet is '.xlsm'. The GUI is an event-driven program that is composed of over 1,000 lines of codes. Multiple windows and dialog boxes are used to collect the necessary input data required to analyze a particular agricultural operation.

The energy model GUI can be launched using a button on the *Instructions*, *Inputs*, or *Outputs* spreadsheets. When the GUI is first launched and there is no prior data entered on the *Inputs* sheet, a message box will prompt the user to enter a name for the new data set (Figure 5.6). This name will be placed in cell D3 of the *Inputs* sheet.

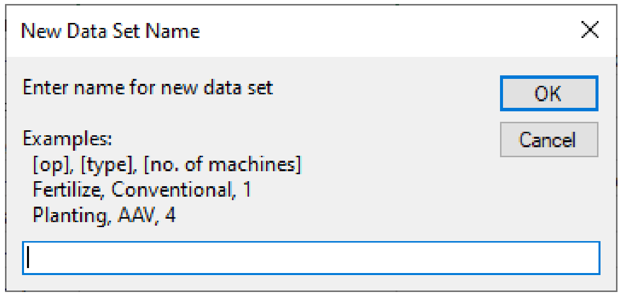
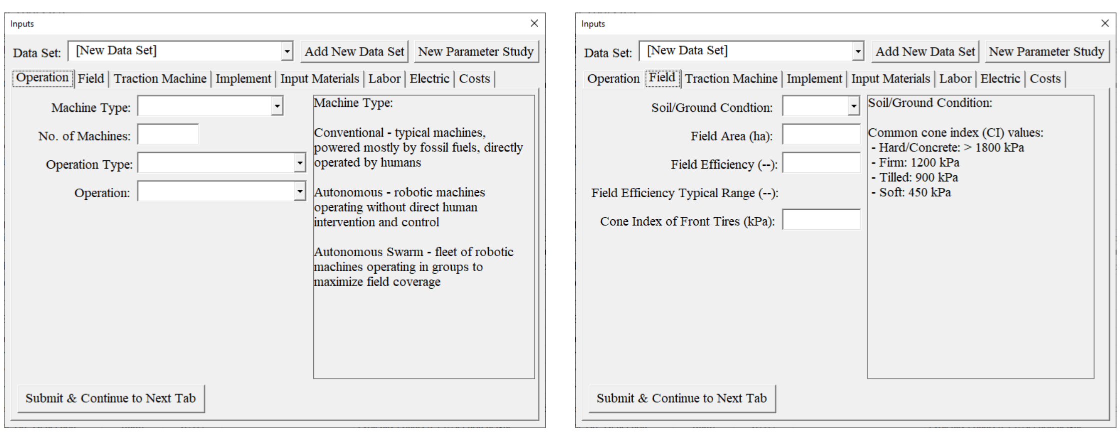


Figure 5.6. Energy model GUI new data set name prompt

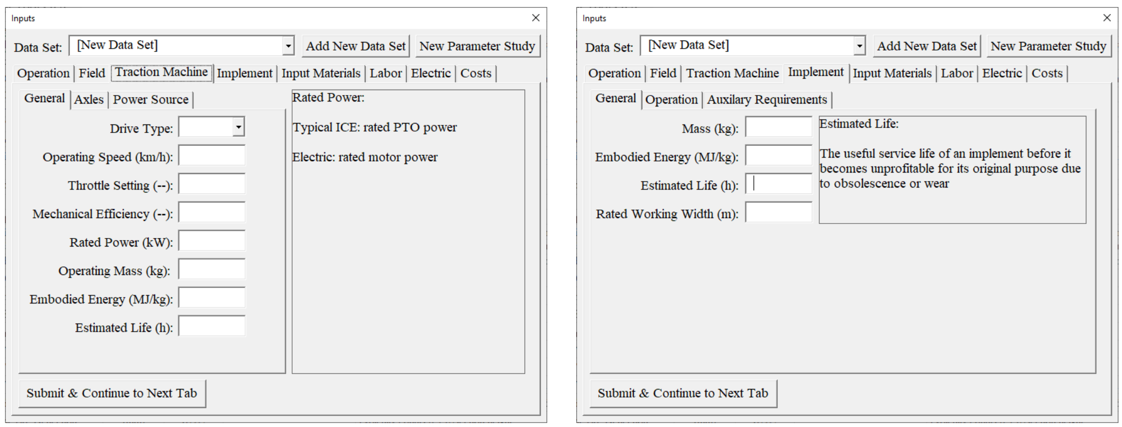
Following the message box prompt, the energy model GUI will open to the first tab (Figure 5.7(a)). The GUI is organized into tabs that help walk the user through the process of entering the necessary data for the agricultural operation analysis; the eight tabs are: *Operation*, *Field*, *Traction Machine*, *Implement*, *Input Materials*, *Labor*, *Electric*, and *Costs*. Within each tab is a set of text boxes and drop down boxes for entering data, along with a *Help Tip* text box that automatically provides helpful information regarding any particular parameter that is being entered. When data is finished being entered on a given tab, the user presses the *Submit & Continue to Next Tab* button; this writes the data to the *Inputs* sheet and advances to the next tab in the GUI.



(a) Energy model GUI *Operations* tab (b) Energy model GUI *Field* tab

Figure 5.7. Energy model GUI - tabs 1 and 2

Data is continually entered as the user moves through the GUI. Some tabs have sub-tabs that help organize the required data together (e.g., Figure 5.8(a)). The user is able to move back forth through the tabs and update values, but the new values will not be confirmed until the *Submit & Continue to Next Tab* button is pressed. When data entry is complete, the energy model GUI can be closed and the results can be viewed on the *Outputs* spreadsheet.



(a) Energy model GUI *Traction Machine* tab

(b) Energy model GUI *Implement* tab

Figure 5.8. Energy model GUI - tabs 3 and 4

5.3 Working with Multiple Data Sets

The energy model Microsoft Excel workbook can be used to analyze multiple data sets at the same time. Each data set is stored as a column on the *Inputs* and *Outputs* spreadsheets. When the energy model workbook is opened for the first time, there are no data sets pre-filled, and the GUI will prompt the user to enter a new data set name (Figure 5.6). The best method for adding more data sets is by pressing the *Add New Data Set* button located at the top of the GUI. This will launch the same user prompt as shown in Figure 5.6. Once the name is confirmed, a new column will be automatically added to the *Inputs* and *Outputs* spreadsheets. Data can then be entered as described above and the results can be viewed.

The inputs associated with each data set can be viewed within the GUI. Using the drop down box at the top of the GUI, the user can select which data set to view and the inputs will automatically populate the text boxes. Changes can be made to these input parameters and saved in the same manner as described above.

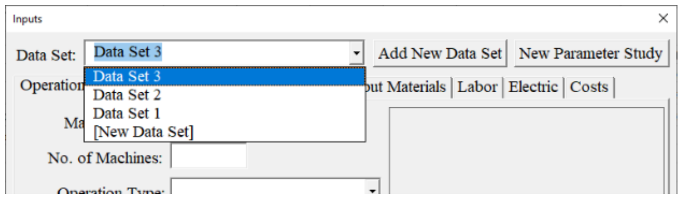


Figure 5.9. Energy model GUI multiple data sets

5.4 Performing Parameter Studies

The final feature of the energy model GUI is to quickly perform parameter studies based off an existing data set. A new parameter study is created by pressing the *New Parameter Study* button at the top of the GUI which launches a new dialog window (Figure 5.10).

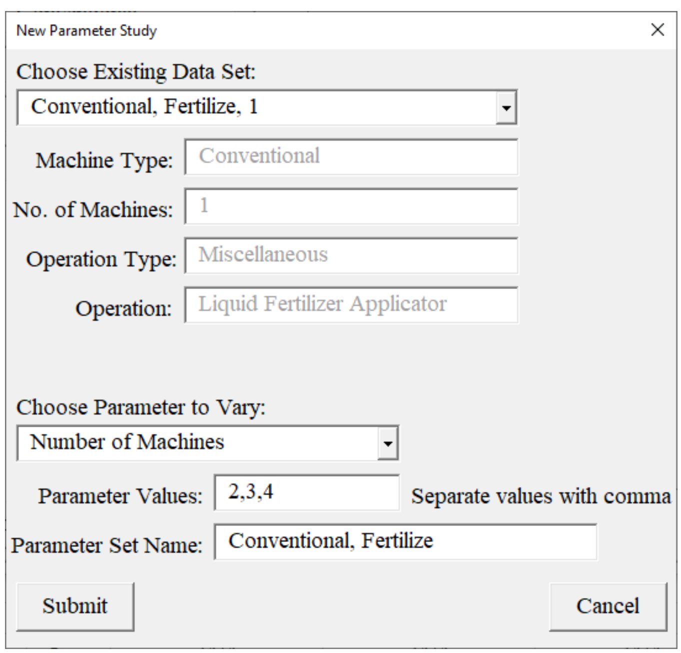


Figure 5.10. Energy model GUI parameter study

The user must first select an existing data set and its general information will be displayed below. Next, a parameter is chosen that is to be varied. Currently, the program is able to vary: number of machines, field efficiency, operating speed, traction machine operating mass, and implement rated working width; however, additional parameters could be added by editing the GUI. Once the desired parameter is selected, the new parameter values are added in the indicated text box. A new parameter set name is given, and then the data sets are automatically created once the *Submit* button is pressed. In the example shown in Figure 5.10, the data set named *'Conventional, Fertilize, 1'* will be used as a reference for a parameter study that varies the number of machines. Three additional data sets will be created where the number of machines will be two, three, and four.

The results from all the data sets are displayed on the *Outputs* worksheet. The method of analyzing and interpreting the results is left up to the user. Because the energy model is built within Microsoft Excel, it is straightforward to create new worksheets, graphs, and tables that can be used to analyze the data sets and results.

6. CONCLUSIONS AND FUTURE WORK

In the years to come, a growing global population will require more crop production than ever before. As technological advances improve across all industries, AAVs can be part of the solution to the rising demand for food. By improving and transforming conventional farming methods, AAVs have the potential to transform the way farming operations are completed. AAVs are a class of robotic machines that have the ability to complete agricultural tasks without requiring direct and constant control of a human operator. By removing the need for an operator, these agricultural robotic machines allow for new vehicle designs and new opportunities for different vehicle configurations and sizes.

This work investigated the effects of AAVs on crop production processes and how they can be used to effectively complete agricultural tasks. A simulation model was developed that calculated the energy requirements of AAVs operating on row crops. This deterministic model was used to quantify the energy needs and energy expenditures of agricultural vehicles and was further used to investigate the effects of using AAVs in lieu of conventional agricultural machinery.

The energy model was designed around four main energy sources for any given in-field operation: traction machine energy source, machinery embodied energy, input material embodied energy, and labor. The model is divided into seven different modules and utilizes user-input, along with prior module data, to generate an output at each step along the way. The architecture of the energy model is shown in Figure 3.2.

The energy model was then demonstrated using a pre-defined scenario of a typical row-crop farming operation in the Midwest U.S. The purpose of the case study was to compare a conventional crop production operation with operations that have implemented autonomous machines. Four general vehicle configurations were chosen based on the traction machine size: large tractor, small tractor, utility vehicle, and single row machines. The complete crop production operation was based on a farm size of 607 ha (1,500 acre) with half the land devoted to corn production. The four main operations were fertilizer application, pesticide spraying, no-till planting, and harvesting.

First, the energy model was used to compare a whole farm operation with three different machine configurations: using all conventional large machines, using all autonomous large machines, and using all autonomous smaller machines (≈55 kW tractor). The results show that from an energy standpoint, the most significant savings comes from the decreased amount of agrochemical application associated with AAVs. The total energy consumption of the large tractor AAV configuration is 36% less than the conventional operation. Besides reduced agrochemical use, little difference is seen between the conventional machinery and large tractor AAVs. Small tractor AAVs fared worse due to the ineffectiveness of smaller combine harvesters. At only four rows wide, the smaller harvester is 1/4 the width of a conventional large combine and requires much more time in the field in order to complete the same task. Yet, the machine size and fuel consumption are not proportionately smaller. Based on these results, it is not recommended to blindly assume that simply switching from large conventional machines to smaller AAVs is the most effective way to save energy and costs.

In order to have a better perspective on the effects of using AAVs, further analysis was conducted on an individual operation basis. Table 4.1 shows the general categories for comparison. The fertilizing operation looked at the outcome of using large conventional machinery, a large tractor AAV, and multiple small tractor AAVs. Because AAVs can work 24-hours per day, the fertilizing operation for the single large tractor AAV could be completed in 1.6 working days, as opposed 2.4 working days for the conventional machine. It only required two small tractor AAVs to meet or exceed the performance of the conventional machine, yet for the same amount of money, four to five small tractor AAVs could be purchased.

The pesticide spraying operation compared five different types of machines. The greatest benefit to utilizing AAVs is the intelligent application of pesticide, which can allow for 65–95% reduction in chemical use. The spraying operation highlighted the advantages of large machines (conventional and autonomous), namely speed of operation and width. Because the large machines are so wide and travel so fast, it takes two small tractor AAVs, seven utility AAVs, or 12 single-row AAVs to match their performance.

The no-till planting operation also compared five different types of machines. Two small tractor AAVs, seven utility AAVs, or 39 single-row AAVs are required to match the performance of conventional machinery. However, for the same cost as the conventional machine, six small tractor AAVs, 16 utility AAVs, or 55 single-row AAVs could be purchased. The benefit of using higher numbers of AAVs is seen in the amount of time required to complete the planting task, where the swarms of AAVs could finish planting in nearly 1/4 of the time.

Harvesting was previously analyzed during the whole farm scenario. In general, the energy consumption and costs are relatively the same between the conventional machine and the large AAV. The advantage of the autonomous harvesting is that is can operate continuously throughout the night. Continuous operation is possible for this scenario because corn can be harvested at night. However, soybeans cannot because the onset of dew at dusk does not allow for proper processing of the crop.

While the completed analysis gives insight and understanding to a common crop production situation, more work is needed to investigate other scenarios. The work presented herein only considered no-till corn production in the Midwest U.S. with four in-field operations per growing season. Additional studies are needed that focus on other crops, agricultural practices, and operations. Additionally, the model could be expanded to include a more holistic analysis of costs and the economics of adopting AAVs. Finally, it is worth noting that the logistics associated with employing AAVs were not considered in this analysis and could play an important role in the decision to utilize dozens of machines rather than a single conventional machine.

Along with the energy model, crop production efficiency metrics were studied that provided an objective method of analyzing the advantages and disadvantages associated with replacing and/or augmenting conventional farming vehicles with AAVs. Energy-per-unit-area shows the amount of energy that is consumed over the entire field, regardless of the task time required. Because labor energy consumption is insignificant compared to the other three inputs, energy-per-unit-area is also independent of the number of machines simultaneously in use. Working days and machinery capital cost are other metrics that proved beneficial when comparing AAVs to conventional machines.

Finally, a modeling tool was developed and demonstrated that allows a user to interact with the energy model in an intuitive way. Creating the modeling tool in Microsoft Excel allows for easy distribution to a wide audience, as opposed to using a more expensive software package. The energy model workbook is composed of five spreadsheets that contain instructions, inputs, outputs, and supporting data tables. A GUI was created using Microsoft Excel VBA that lets the user interact with an event-driven program. Data sets can easily be created and modified for the purpose of evaluating different farming operations. Additionally, options within the GUI allow for parameter studies where multiple data sets can be instantly created in order to analyze the effects of changing a single variable. Areas for improvement to the spreadsheet and GUI could include additional parameters that are available to vary, a method of automatically generating charts, or the process of creating tables to succinctly summarize the results.

In the years to come, a growing global population indicate a need for increased crop production. Societal elements, such as a decreased labor force, and environmental effects show the importance of continuing to push the envelope and evolve farming practices and machinery applications. This research identified key areas of vehicle improvement and new farming methods for the purpose of increasing efficiencies, reducing the overall environmental impact of farming, and taking advantage of the next generation of agricultural machines.

REFERENCES

Agerholm, H. (2018). Uk crops left to rot after drop in eu farm workers in britain after brexit referendum. February 5, 2018. [Online]. Retrieved from http://unbonmotgroundswell.blogspot.com/2014/09/a-nimble-wheeled-farm-robot-goes-to.html.

Aguilera, E., Guzmn, G. I., Infante-Amate, J., Soto, D., Garca-Ruiz, R., Herrera, A., Villa, I., Torremocha, E., Carranza, G., and de Molina, M. G. (2015). Embodied energy in agricultural inputs. Incorporating a historical perspective. Documentos de Trabajo de la Sociedad Espaola de Historia Agraria 1507, Sociedad Espaola de Historia Agraria.

Alexandratos, N., Bruinsma, J., et al. (2012). World agriculture towards 2030/2050: the 2012 revision. Technical report, ESA Working paper FAO, Rome.

Ali, M. B. and McBride, W. D. (1994). Soybeans: State-level produciton costs, characteristics, and input use, 1990. Technical Report 1487-2016-122359, USDA Economic Research Service, 1994-02.

Alsalam, B. H. Y., Morton, K., Campbell, D., and Gonzalez, F. (2017). Autonomous uav with vision based on-board decision making for remote sensing and precision agriculture. In *2017 IEEE Aerospace Conference*, pages 1–12.

Araújo, K., Mahajan, D., Kerr, R., and Silva, M. d. (2017). Global biofuels at the crossroads: An overview of technical, policy, and investment complexities in the sustainability of biofuel development. *Agriculture*, 7(32).

ASABE (2015a). *ASAE D497.7 MAR2011 (R2015) Agricultural Machinery Management Data*. ASABE, St. Joseph, MI, USA.

ASABE (2015b). *ASAE EP496.3 FEB2006 (R2015) Cor.1 Agricultural Machinery Management Data*. ASABE, St. Joseph, MI, USA.

Bac, C. W., van Henten, E. J., Hemmings, J., and Edan, Y. (2014). Harvesting robots for high-value crops: State-of-the-art review and challenges ahead. *Journal of Field Robotics*, 31:888–911. doi:10.1002/rob.21525.

Bakker, T., Asselt, K., Bontsema, J., Müller, J., and Straten, G. (2010). Systematic design of an autonomous platform for robotic weeding. *Journal of Terramechanics*, 47(2):67–73.

Ball, D., Ross, P., English, A., Patten, T., Upcroft, B., Fitch, R., Sukkarieh, S., Wyeth, G., and Corke, P. (2015). *Robotics for Sustainable Broad-Acre Agriculture*, pages 439–453. Springer International Publishing, Cham.

Bargoti, S., Underwood, J. P., Nieto, J. I., and Sukkarieh, S. (2015). *A Pipeline for Trunk Localisation Using LiDAR in Trellis Structured Orchards*, pages 455–468. Springer International Publishing, Cham.

Barker, T. (2016). Yorkton brothers win ag tech contest. `https://www.yorktonthisweek.com/news/local-news/yorkton-brothers-win-ag-tech-contest-1.2258150`. Online; accessed 17-June-2019.

Basso, B., Shuai, G., Zhang, J., and Robertson, G. P. (2019). Yield stability analysis reveals sources of large-scale nitrogen loss from the us midwest. *Scientific Reports*, 9(5774).

Baxter, J. A., Merced, D. A., Costinett, D. J., Tolbert, L. M., and Ozpineci, B. (2018). Review of electrical architectures and power requirements for automated vehicles. In *2018 IEEE Transportation Electrification Conference and Expo (ITEC)*, pages 944–949.

Bechar, A. and Vigneault, C. (2016). Agricultural robots for field operations: Concepts and components. *Biosystems Engineering*, 149:94–111.

Bellarby, J., Foereid, B., Hastings, A., and Smith, P. (2008). *Cool Farming: Climate impacts of agriculture and mitigation potential.* Greenpeace Int., Amsterdam, Netherlands.

Billingsley, J. and Schoenfisch, M. (1997). The successful development of a vision guidance system for agriculture. *Computers and Electronics in Agriculture*, 16(2):147–163.

Blackmore, B. and Griepentrog, H. (2006). Section 4.3 autonomous vehicles and robots. In CIGR The International Commission of Agricultural Engineering, editor, *CIGR Handbook of Agriclutural Engineering Volume VI Information Technology*, chapter 4, pages 204–2015. ASABE, St. Joseph, Michigan, USA.

Bochtis, D. and Srensen, C. (2009). The vehicle routing problem in field logistics part i. *Biosystems Engineering*, 104(4):447–457.

Boglietti, A., Cavagnino, A., Lazzari, M., and Pastorelli, M. (2003). International standards for the induction motor efficiency evaluation: a critical analysis of the stray-load loss determination. In *38th IAS Annual Meeting on Conference Record of the Industry Applications Conference, 2003.*, volume 2, pages 841–848 vol.2.

Bonadies, S., Lefcourt, A., and Gadsden, S. (2016). A survey of unmanned ground vehicles with applications to agricultural and environmental sensing. In Valasek, J. and Thomasson, J., editors, *Autonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping*, volume 9866, page 98660Q. SPIE, Bellingham, Washington, USA.

Bongiovanni, R. and Lowenberg-Deboer, J. (2004). Precision agriculture and sustainability. *Precision Agriculture*, 5(4):359–387.

Bosch (2017). Bonirob. `https://www.deepfield-robotics.com/en/`.

Busse, W., Coenenberg, H., Feldman, F., and Crusinberry, T. F. (1977). *The first serial produced automatic steering system for corn combines and forage harvesters.* Proceedings of the International Grain and Forage Harvesting Conference, Ames, IA. pages 43-47.

Campanari, S., Manzolini, G., and de la Iglesia, F. G. (2009). Energy analysis of electric vehicles using batteries or fuel cells through well-to-wheel driving cycle simulations. *Journal of Power Sources*, 186(2):464 – 477.

Case IH (2017). Autonomous concept vehicle. https://www.caseih.com/northamerica/en-us/Pages/campaigns/autonomous-concept-vehicle.aspx. Online; accessed 21-May-2019.

Case IH (2018). Case ih deines categories of autonomy and announces pilot programme. https://media.cnhindustrial.com/EUROPE/CASE-IH/ALL/case-ih-defines-categories-of-autonomy-and-announces-pilot-programme/s/e59e8bca-1e92-4b48-8aa7-16a0588ee258. Online; accessed 22-May-2019.

Cavender-Bares, K. (2018). Demo Day 2018 - Hosted By Google. Uploaded March 28, 2018. Retrieved from https://www.youtube.com/watch?v=ZeNkqfqynbg. Time: 52:09 - 1:00:10.

De, A., Bose, R., Kumar, A., and Mozumdar, S. (2014). Worldwide pesticide use. In *Targeted Delivery of Pesticides Using Biodegradable Polymeric Nanoparticles*, pages 5–6. Springer India, New Delhi.

De-An, Z., Jidong, L., Wei, J., Ying, Z., and Yu, C. (2011). Design and control of an apple harvesting robot. *Biosystems Engineering*, 110(2):112 – 122.

DJI (2018). Dji - the future of possible. Retrieved from https://www.dji.com/.

Edwards, W. (2015). Estimating farm machinery costs. *Iowa State University Ag Decision Maker*. File A3-29.

FAO (2017). Faostat database. Rome, Italy.

Fendt (2017). Fendt puts the new 'xaver' to use. `https://www.fendt.com/int/fendt-xaver.html`. Online; accessed 17-June-2019.

Freeman, P. K. and Freeland, R. S. (2015). Agricultural uavs in the u.s.: potential, policy, and hype. *Remote Sensing Applications: Society and Environment*, 2:35–43.

Friedrich, T. and Kassam, A. (2016). Food security as a function of sustainable intensification of crop production. *AIMS Agriculture and Food*, 1(2):227–238.

Gawron, J. H., Keoleian, G. A., De Kleine, R. D., Wallington, T. J., and Kim, H. C. (2018). Life cycle assessment of connected and automated vehicles: Sensing and computing subsystem and vehicle level effects. *Environmental Science & Technology*, 52(5):3249–3256. PMID: 29446302.

Gellings, C. W. and Parmenter, K. E. (2009). Energy efficiency in fertilizer production and use. In Gellings, C. W., editor, *Efficient use and conservation of energy*, volume 2, pages 123–136. EOLSS Publishers, Oxford, United Kingdom.

Gleick, P. H., Ajami, N., Christian-Smith, J., Cooley, H., Donnelly, K., Fulton, J., Ha, M.-L., Heberger, M., Moore, E., Morrison, J., Orr, S., Schulte, P., and Srinivasan, V. (2014). *The World's Water The Biennial Report on Freshwater Resouces*, volume 8, page 5. Island Press, Washington, DC.

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., and Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people. *Science*, 327(5967):812–818.

Goering, C. E., Stone, M. L., Smith, D. W., and Turnquist, P. K. (2003). *Off-road vehicle engineering principles*. ASAE, St. Joseph, MI. page 371.

Gonzalez-de Santos, P., Ribeiro, A., Fernandez-Quintanilla, C., Lopez-Granados, F., Brandstoetter, M., Tomic, S., Pedrazzi, S., Peruzzi, A., Pajares, G., Kaplanis, G., Perez-Ruiz, M., Valero, C., del Cerro, J., Vieri, M., Rabatel, G., and Debilde, B. (2017). Fleets of robots for environmentally-safe pest control in agriculture. *Precision Agriculture*, 18(4):574–614.

Gonzalez-de Soto, M., Emmi, L., Perez-Ruiz, M., Aguera, J., and Gonzalez-de Santos, P. (2016). Autonomous systems for precise spraying – evaluation of a robotised patch sprayer. *Biosystems Engineering*, 146:165–182.

Grisso, R. D., Vaughan, D. H., and Roberson, G. T. (2008). Fuel prediction for specific tractor models. *Applied Engineering in Agriculture*, 24(4):423–428.

Grounds, T. (2014). A nimble-wheeled farm robot goes to work in minnesota. September 10, 2014. [Online]. Retrieved from `http://unbonmotgroundswell.blogspot.com/2014/09/a-nimble-wheeled-farm-robot-goes-to.html`.

Hague, T., Marchant, J., and Tillett, N. (2000). Ground based sensing systems for autonomous agricultural vehicles. *Computers and Electronics in Agriculture*, 25:11–28.

Harries, G. O. and Ambler, B. (1981). Automatic ploughing: A tractor guidance system using opto-electronic remote sensing techniques and a microprocessor based controller. *Journal of Agricultural Engineering Research*, 26(1):33–53.

Hawkins, A. J. (2017). Not all of our self-driving cars will be electrically powered–here's why. `https://www.theverge.com/2017/12/12/16748024/self-driving-electric-hybrid-ev-av-gm-ford`. Online; accessed 22-May-2019.

Hayes, J. G., de Oliveira, R. P. R., Vaughan, S., and Egan, M. G. (2011). Simplified electric vehicle power train models and range estimation. In *2011 IEEE Vehicle Power and Propulsion Conference*, pages 1–5.

Heraud, J. A. and Lange, A. F. (2009). *Agricultural Automatic Vehicle Guidance from Horses to GPS: How We Got here, and Where We Are Going.* Agricultural Equipment Technology Conference, Louisville, KY. ASABE Distinguished Lecture No. 33.

Hertz, T. and Zahniser, S. (2012). Is there a farm labor shortage? *American Journal of Agricultural Economics*, 95(2):476–481.

Hofman, T. and Dai, C. H. (2010). Energy efficiency analysis and comparison of transmission technologies for an electric vehicle. In *2010 IEEE Vehicle Power and Propulsion Conference*, pages 1–6.

Hunt, D. and Wilson, D. (2016). *Farm Power & Machinery Management*, chapter 1, pages 5–6. Waveland Press, Inc., Long Grove, IL, USA, 11 edition.

Ibarrola-Rivas, M. J., Kastner, T., and Nonhebel, S. (2016). How much time does a farmer spend to produce my food? an international comparison of the impact of diets and mechanization. *Resources*, 5(4).

Iida, M., Suguri, M., Uchida, R., Ishibashi, M., Kurita, H., Won-Jae, C., Masuda, R., and Ohdoi, K. (2013). Advanced harvesting system by using a combine robot. *IFAC Proceedings Volumes*, 46(4):40–44. 5th IFAC Conference on Bio-Robotics.

Keyzer, M., Merbis, M., Pavel, I., and van Wesenbeeck, C. (2005). Diet shifts towards meat and the effects on cereal use: can we feed the animals in 2030? *Ecological Economics*, 55(2):187–202.

Kirk, T. G. (1974). A furrow-following tractor guidance system. Master's thesis, University of Saskatchewan, Saskatoon, Saskatchewan.

Kitani, O., Jungbluth, T., Peart, R., and Ramdani, A. (1999). Volume v: Energy and biomass engineering. In *CIGR Handbook of Agricultural Engineering*. The International Commission of Agricultural Engineering, Kyoto, Japan.

Larson, P. D., Vifara, J., Parsons, R. V., and Elias, A. (2014). Consumer attitudes about electric cars: Pricing analysis and policy implications. *Transportation Research Part A: Policy and Practice*, 69:299 – 314.

Mecrow, B. and Jack, A. (2008). Efficiency trends in electric machines and drives. *Energy Policy*, 36(12):4336 – 4341. Foresight Sustainable Energy Management and the Built Environment Project.

Mrema, G., Soni, P., and Rolle, R. S. (2015). *A Regional Strategy for Sustainable Agricultural Mechanization. Sustainable Mechanization across Agri-Food Chains in Asia and the Pacific region.* Food and Agricultural Organization of the United Nations (FAO). FAO Regional Office for Asia and the Pacific Publication 2014/24.

NASS (2018). Farm labor. Technical report, USDA National Agricultural Statistics Service. ISSN: 1949-0909.

Nørremark, M., Griepentrog, H. W., Nielsen, J., and Søgaard, H. T. (2012). Evaluation of an autonomous gps-based system for intra-row weed control by assessing the tilled area. *Precision Agriculture*, 13(2):149–162.

OECD (2016). Biofuels. In *OECD-FAO Agricultural Outlook 2016-2025*. OECD Publishing, Paris. `http://dx.doi.org/10.1787/agr_outlook-2016-13-en`.

Pajares, G., Garca-Santilln, I., Campos, Y., Montalvo, M., Guerrero, J. M., Emmi, L., Romeo, J., Guijarro, M., and Gonzalez-de Santos, P. (2016). Machine-vision systems selection for agricultural vehicles: A guide. *Journal of Imaging*, 2(4).

Pedersen, S., Fountas, S., Have, H., and Blackmore, B. (2006). Agricultural robots—system analysis and economic feasibility. *Precision Agriculture*, 7(4):295–308.

Petersen, B. and Snapp, S. (2015). What is sustainable intensification? Views from experts. *Land Use Policy*, 46:1–10.

Pimentel, D. (2009). Energy inputs in food crop production in developing and developed nations. *Energies*, 2(1):1–24.

Pimentel, D. and Pimentel, M. H. (2008). *Food, Energy, and Society.* CRC Press, Boca Raton, FL, 3 edition.

Pomeroy, W., Wilhoit, J., and Swetnam, L. (2014). *Assessing a Mechanical Furrow-Following System to Obtain Multiple Pass Precision Guidance for Vegetable Production.* ASABE and CSBE/SCGAB Annual International Meeting, Montreal, Quebec. Paper Number: 1908802.

Pretty, J. (2008). Agricultural sustainability: concepts, principles and evidence. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 363(1491):447–465.

Ramankutty, N., Evan, A. T., Monfreda, C., and Foley, J. A. (2008). Farming the planet: 1. geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, 22(1).

Ramankutty, N., Mehrabi, Z., Waha, K., Jarvis, L., Kremen, C., Herrero, M., and Rieseberg, L. H. (2018). Trends in global agricultural land use: Implications for environmental health and food security. *Annual Review of Plant Biology*, 69(1):789–815. PMID: 29489395.

Ray, D. K., Mueller, N. D., West, P. C., and Foley, J. A. (2013). Yield trends are insufficient to double global crop production by 2050. *PLOS ONE*, 8(6):1–8.

Redpath, D. A., McIlveen-Wright, D., Kattakayam, T., Hewitt, N. J., Karlowski, J., and Bardi, U. (2011). Battery powered electric vehicles charged via solar photovoltaic arrays developed for light agricultural duties in remote hilly areas in the southern mediterranean region. *Journal of Cleaner Production*, 19(17):2034 – 2048.

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., Wetterstrand, H., DeClerck, F., Shah, M., Steduto, P., de Fraiture, C., Hatibu, N., Unver, O., Bird, J., Sibanda, L., and Smith, J. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. *Ambio*, 46(1):4–17.

Rodias, E., Berruto, R., Bochtis, D., Busato, P., and Sopegno, A. (2017). A computational tool for comparative energy cost analysis of multiple-crop production systems. *Energies*, 10(7). Article no. 831.

Roldán, J. J., Cerro, J. D., Garzón-Ramos, D., Garcia-Aunon, P., Garzón, M., León, J. D., and Barrientos, A. (2018). Robots in agriculture: State of art and practical experiences. In Neves, A., editor, *Service Robots*, chapter 4. InTech, Rijeka.

Ruckelshausen, A., Biber, P., Dorna, M., Gremmes, H., Klose, R., Linz, A., Rahe, R., Resch, R., Thiel, M., Trautz, D., and Weiss, U. (2009). Bonirob: an autonomous field robot platform for individual plant phenotyping. In van Henten, E., Goense, D., and Lokhorst, C., editors, *Precision Agriculture '09*, pages 841–847. Wageningen Academic Publishers, Wageningen, Netherlands.

Ružić, D. and Časnji, F. (2011). Agricultural tractor cab characteristics relevant for microclimatic conditions. *Journal of Applied Engineering Science*, 9(2):323–330.

SAE International (2018). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles*.

Sakai, S., Iida, M., Osuka, K., and Umeda, M. (2008). Design and control of a heavy material handling manipulator for agricultural robots. *Autonomous Robots*, 25(3):189–204.

Schmale, D., Dingus, B., and Reinholtz, C. (2008). Development and application of an autonomous unmanned aerial vehicle for precise aerobiological sampling above agricultural fields. *Journal of Field Robotics*, 25(3):133–147.

Scholz, C., Kohlbrecher, M., and Ruckelshausen, A. (2014). Camera-based selective weed control application module ("precision spraying app") for the autonomous field robot platform bonirob. In *Proceedings of the International Conference of Agricultural Engineering*, Zurich, Switzerland. Ref: C0598.

Searcy, S. W., Schueller, J. K., H., B. Y., and Stout, B. A. (1990). Measurement of agricultural field location using microwave frequency triangulation. *Computers and Electronics in Agriculture*, 4:209–223.

Sopegno, A., Rodias, E., Bochtis, D., Busato, P., Berruto, R., Boero, V., and Sørensen, C. (2016). Model for energy analysis of miscanthus production and transportation. *Energies*, 9(6). Article no. 392.

Stafford, J. V. (2000). Implementing precision agriculture in the 21st century. *Journal of Agricultural Engineering Research*, 25(3):267–275.

Stewart, W. M., Dibb, D. W., Johnston, A. E., and Smyth, T. J. (2005). The Contribution of Commercial Fertilizer Nutrients to Food Production. *Agronomy Journal*, 97.

Stombaugh, T. (2018). Satellite-based positioning systems for precision agriculture. In Shannon, D., Clay, D., and Kitchen, N., editors, *Precision Agriculture Basics*, chapter 3, pages 25–36. ASA, CSSA, and SSSA, Madison, WI. doi:10.2134/precisionagbasics.2017.0036.

Suprem, A., Mahalik, N., and Kim, K. (2013). A review on application of technology systems, standards and interfaces for agriculture and food sector. *Computer Standards & Interfaces*, 35(4):355 – 364.

Swetnam, L. D., Casada, J. H., and Walton, L. R. (1981). Burley tobacco harvesting aid. *Transactions of the ASAE*, 24(5):1111–1113, 1121.

Talbot, D. (2014). A nimbled-wheeled farm robot goes to work in minnesota. MIT Technology Review. September 9, 2014. [Online]. `https://www.technologyreview.com/s/530526/a-nimble-wheeled-farm-robot-goes-to-work-in-minnesota`.

Taylor, J., Charlton, D., and Yùnez-Naude, A. (2012). The end of farm labor. *Applied Economic Perspectives and Policy*, 34(4):587–598.

Tillett, N., Hague, T., Gundy, A., and Dedousis, A. (2008). Mechanical within-row weed control for transplanted crops using computer vision. *Biosystems Engineering*, 99(2):171–178.

Tillett, N. D. (1991). Automatic guidance sensors for agricultural field machines: A review. *Journal of Agricultural Engineering Research*, 50:167–187.

Tilman, D., Balzer, C., Hill, J., and Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences*, 108(50):20260–20264.

Torres-Sospedra, J. and Nebot, P. (2014). Two-stage procedure based on smoothed ensembles of neural networks applied to weed detection in orange groves. *Biosystems Engineering*, 123:40 – 55.

UNEP (2014). Assessing global land use: Balancing consumption with sustainable supply. Technical report, United Nations Environment Programme.

United Nations, Department of Economic and Social Affairs, Population Division (2017). World Population Prospects: The 2017 revision. `https://esa.un.org/unpd/wpp/`.

Väljaots, E. (2017). *Energy Efficiency Evaluation Method for Mobile Robot Platform Design*. PhD thesis, Tallinn University of Technology, Tallinn, Estonia.

Väljaots, E., Lehiste, H., Kiik, M., and Leemet, T. (2018). Soil sampling automation using mobile robotic platform. *Agronomy Research*, 16(3):917–922.

Van Vuuren, D. and Faber, A. (2009). Growing within Limits: A Report to the Global Assembly 2009 of the Club of Rome. Technical report, Netherlands Environmental Assessment Agency PBL, Bilthoven (Netherlands). PBL–500201001.

Weiss, U. and Biber, P. (2011). Plant detection and mapping for agricultural robots using a 3d lidar sensor. *Robotics and Autonomous Systems*, 59(5):265 – 273. Special Issue ECMR 2009.

Wells, C. (2001). Total energy indicators of agricultural sustainability: Dairy farming case study. Technical Report 3, Ministry of Agriculture and Forestry, Wellington, New Zealand.

Widden, M. B. and Blair, J. R. (1972). A new automatic tractor guidance system. *Journal of Agricultural Engineering Research*, 17(1):10–21.

Williamson, S., Lukic, M., and Emadi, A. (2006). Comprehensive drive train efficiency analysis of hybrid electric and fuel cell vehicles based on motor-controller efficiency modeling. *IEEE Transactions on Power Electronics*, 21(3):730–740.

Wilson, J. N. (2000). Guidance of agricultural vehicles – a historical perspective. *Computers and Electronics in Agriculture*, 25:3–9.

Xiang, H. and Tian, L. (2006). *Development of autonomous unmanned helicopter based agricultural remote sensing system.* ASABE Annual International Meeting, Portland, Oregon, USA. Paper Number: 063097.

Zhang, C. and Kovacs, J. M. (2012). The application of small unmanned aerial systems for precision agriculture: a review. *Precision Agriculture*, 13(6):693–712.

Zhang, S. (2016). A chemical reaction revolutionized farming 100 years ago. now it needs to go. `https://www.wired.com/2016/05/chemical-reaction-revolutionized-farming-100-years-ago-now-needs-go/`.

APPENDICES

A. SIMULATION AND APPLICATION OF MODEL - INPUT PARAMETERS

A.1 Whole Farm - Conventional Agricultural Operation

	A	B	C	D	E	F	G
1	Launch Modeling Tool GUI						
2							
3	**Name**	**Units**	**Symbol**	**Fertilizer**	**Herbicide**	**Planting**	**Harvest**
4		[--]	[--]	Conventional	Conventional	Conventional	Conventional
5	No. of Machines	[--]	$n_{machines}$	1	1	1	1
6	Machines per Operator	[--]	n_{MpO}	1	1	1	1
7	Soil/Ground Condition	[--]	[--]	Firm	Firm	Firm	Firm
8	Field Area	[ha]	a	300	300	300	300
9	Operation Type	[--]	[--]	Miscellaneous	Miscellaneous	Planting	Harvesting
10	Operation	[--]	[--]	Liquid Fertilizer Applicator	Boom-type sprayer	Row crop planter	Combine (SP)
11	Field Efficiency	[--]	E_f	0.65	0.65	0.65	0.7
12							
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel	Fossil Fuel	Fossil Fuel	Fossil Fuel
14	Traction Machine Drive Type	[--]	[--]	MFWD	MFWD	MFWD	2WD
15	Traction Machine Operating Speed	[km/h]	s	10.5	11.2654	8	6.6
16	Traction Machine Engine Throttle Ratio	[--]	N	0.8	0.75	0.8	1
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96	0.96	0.96	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	187	54.35	187	240
19	Traction Machine Operating Mass	[kg]	m_{TM}	11678	3784.5	11678	23000
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138	138	138	116
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	16000	16000	16000	3000
22	Traction Machine Front Tire Type	[--]	[--]	Radial Ply	Radial Ply	Radial Ply	Radial Ply
23	Traction Machine Front Tire Configureation	[--]	[--]	1	1	1	2
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	480	280	480	520
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	336	238	336	442
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	1434	1111	1434	1950.8
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	63.84	45.22	63.84	83.98
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	4831	1513.8	4831	13800
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200	1200	1200	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Radial Ply	Radial Ply	Radial Ply	Radial Ply
31	Traction Machine Rear Tire Configureation	[--]	[--]	2	1	2	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	480	420	480	420
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	384	357	384	357
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	1936.4	1476	1936.4	1374.4
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	72.96	67.83	72.96	67.83
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	6847	2270.7	6847	9200
37							
38	Implement Mass	[kg]	m_{imp}	8820	1324.5	9610	0
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	129	129	133	0
40	Implement Estimated Life	[h]	$t_{life,imp}$	1200	1500	1500	0
41	Implement Rated Working Width	[m]	w	11.43	12.192	9.144	9.144
42	Implement Electrical Current	[A]	i	0	0	0	0
43	Implement Electrical Voltage	[V]	V	0	0	0	0
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0	0	0	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0	0	0	0
46	Implement Rotary Operation Machine	[--]	[--]	None	None	None	Combine, corn
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0	0	0	46.40332768
48	Implement Type	[--]	[--]	Other Seeding	None	Row Crop Planter	None
49	Implement	[--]	[--]	Nitrogen Applicator		No-till, Seeding only - 1 fluted coulter/row	None
50	Implement Width Units	[--]	[--]			rows	
51	Implement Width	[--]	w_{imp}	15	0	12	0
52	Implement Tillage Depth	[cm]	T_{depth}	1	0	1	0
53	Soil Texture Type	[--]	[--]	Medium	Medium	Medium	Medium
54							
55	Planting Rate	[seed/ha]	r_{plant}	0	0	82780	0
56	Planting Material Density	[seed/kg]	ρ_{plant}	0	0	5000	0
57	Planting Energy Content	[MJ/kg]	e_{plant}	0	0	104	0
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	100	0	0	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	78	0	0	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0	0.56	0	0
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	0	85	0	0
62							
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2	41.2	41.2	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46	46	46	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2	2.2	2.2	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	16	16	16	16
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	16	16	16	16
68							
69	Charging Station Efficiency	[--]	η_{cs}	0.95	0.95	0.95	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95	0.95	0.95	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8	0.8	0.8	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7	0.7	0.7	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$				
74	Electric Charge Time	[h]	$t_{elec,charge}$				
75							
76	Fuel Price	[$/L]	p_{fuel}	0.665713886	0.665713886	0.665713886	0.67
77	Lubrication Price	[$/L]	p_{lube}	6.35	6.35	6.35	6.35
78	Electricity Price	[$/kW·h]	p_{elec}	0.13	0.13	0.13	0.13
79	Traction Machine Price	[$]	p_{TM}	300000	51590	300000	430000
80	Implement Price	[$]	p_{imp}	50000	66511	124950	0
81	Planting Material Price	[$/kg]	p_{plant}	17	17	17	17.00
82	Fertilizer Price	[$/kg]	p_{fert}	0.78	0.78	0.78	0.78
83	Pesticide Price	[$/kg]	p_{pest}	16.5	16.5	16.5	16.50
84	Labor Wage	[$/h]	p_{labor}	15	15	15	15.00

A.2 Whole Farm - AAV - Configuration 1

	A	B	C	D	E	F	G
1	Launch Modeling Tool GUI						
2							
3	**Name**	**Units**	**Symbol**	**Fertilizer**	**Herbicide**	**Planting**	**Harvest**
4		[--]	[--]	Autonomous	Autonomous	Autonomous	Autonomous
5	No. of Machines	[--]	$n_{machines}$	1	1	1	1
6	Machines per Operator	[--]	n_{MpO}	1	1	1	1
7	Soil/Ground Condition	[--]	[--]	Firm	Firm	Firm	Firm
8	Field Area	[ha]	a	300	300	300	300
9	Operation Type	[--]	[--]	Miscellaneous	Miscellaneous	Planting	Harvesting
10	Operation	[--]	[--]	Liquid Fertilizer Applicator	Boom-type sprayer	Row crop planter	Combine (SP)
11	Field Efficiency	[--]	E_f	0.65	0.65	0.65	0.7
12							
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel	Fossil Fuel	Fossil Fuel	Fossil Fuel
14	Traction Machine Drive Type	[--]	[--]	MFWD	MFWD	MFWD	2WD
15	Traction Machine Operating Speed	[km/h]	s	10.5	11.2654	8	6.6
16	Traction Machine Engine Throttle Ratio	[--]	N	0.8	0.75	0.8	1
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96	0.96	0.96	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	187	54.35	187	240
19	Traction Machine Operating Mass	[kg]	m_{TM}	10510.2	4205	10510.2	21520.4
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138	138	138	116
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	16000	16000	16000	3000
22	Traction Machine Front Tire Type	[--]	[--]	Radial Ply	Radial Ply	Radial Ply	Radial Ply
23	Traction Machine Front Tire Configureation	[--]	[--]	1	1	1	2
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	480	280	480	520
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	336	238	336	442
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	1434	1111	1434	1950.8
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	63.84	45.22	63.84	83.98
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	4347.9	1682	4347.9	12912.24
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200	1200	1200	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Radial Ply	Radial Ply	Radial Ply	Radial Ply
31	Traction Machine Rear Tire Configureation	[--]	[--]	2	1	2	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	480	420	480	420
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	384	357	384	357
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	1936.4	1476	1936.4	1374.4
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	72.96	67.83	72.96	67.83
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	6162.3	2523	6162.3	8608.16
37							
38	Implement Mass	[kg]	m_{imp}	8820	1324.5	9610	0
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	129	129	133	0
40	Implement Estimated Life	[h]	$t_{life,imp}$	1200	1500	1500	0
41	Implement Rated Working Width	[m]	w	11.43	12.192	9.144	9.144
42	Implement Electrical Current	[A]	i	0	0	0	0
43	Implement Electrical Voltage	[V]	V	0	0	0	0
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0	0	0	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0	0	0	0
46	Implement Rotary Operation Machine	[--]	[--]	None	None	None	Combine, corn
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0	0	0	46.40332768
48	Implement Type	[--]	[--]	Other Seeding	None	Row Crop Planter	None
49	Implement	[--]	[--]	Nitrogen Applicator		No-till, Seeding only - 1 fluted coulter/row	None
50	Implement Width Units	[--]	[--]				
51	Implement Width	[--]	w_{imp}	15	0	12	0
52	Implement Tillage Depth	[cm]	T_{depth}	1	0	1	0
53	Soil Texture Type	[--]	[--]	Medium	Medium	Medium	Medium
54							
55	Planting Rate	[seed/ha]	r_{plant}	0	0	82780	0
56	Planting Material Density	[seed/kg]	ρ_{plant}	0	0	5000	0
57	Planting Energy Content	[MJ/kg]	e_{plant}	0	0	104	0
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	50	0	0	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	78	0	0	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0	0.2	0	0
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	0	85	0	0
62							
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2	41.2	41.2	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46	46	46	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2	2.2	2.2	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	24	24	24	24
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	12	12	12	12
68							
69	Charging Station Efficiency	[--]	η_{cs}	0.95	0.95	0.95	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95	0.95	0.95	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8	0.8	0.8	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7	0.7	0.7	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$				
74	Electric Charge Time	[h]	$t_{elec,charge}$				
75							
76	Fuel Price	[$/L]	p_{fuel}	0.665713886	0.665713886	0.665713886	0.67
77	Lubrication Price	[$/L]	p_{lube}	6.35	6.35	6.35	6.35
78	Electricity Price	[$/kW·h]	p_{elec}	0.13	0.13	0.13	0.13
79	Traction Machine Price	[$]	p_{TM}	330000	56749	330000	473000
80	Implement Price	[$]	p_{imp}	50000	66511	124950	0
81	Planting Material Price	[$/kg]	p_{plant}	17	17	17	17.00
82	Fertilizer Price	[$/kg]	p_{fert}	0.78	0.78	0.78	0.78
83	Pesticide Price	[$/kg]	p_{pest}	16.5	16.5	16.5	16.50
84	Labor Wage	[$/h]	p_{labor}	15	15	15	15.00

A.3 Whole Farm - AAV - Configuration 2

	A	B	C	D	E	F	G
1	Launch Modeling Tool GUI						
2							
3	**Name**	**Units**	**Symbol**	**Fertilizer**	**Herbicide**	**Planting**	**Harvest**
4	Machine Type	[--]	[--]	Autonomous	Autonomous	Autonomous	Autonomous
5	No. of Machines	[--]	$n_{machines}$	1	1	1	1
6	Machines per Operator	[--]	n_{MpO}	1	1	1	1
7	Soil/Ground Condition	[--]	[--]	Firm	Firm	Firm	Firm
8	Field Area	[ha]	a	300	300	300	300
9	Operation Type	[--]	[--]	Miscellaneous	Miscellaneous	Planting	Harvesting
10	Operation	[--]	[--]	Liquid Fertilizer Applicator	Boom-type sprayer	Row crop planter	Combine (SP)
11	Field Efficiency	[--]	E_f	0.65	0.65	0.65	0.7
12							
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel	Fossil Fuel	Fossil Fuel	Fossil Fuel
14	Traction Machine Drive Type	[--]	[--]	MFWD	MFWD	MFWD	2WD
15	Traction Machine Operating Speed	[km/h]	s	10.5	11.2654	8	6.6
16	Traction Machine Engine Throttle Ratio	[--]	N	0.75	0.75	0.5	0.95
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96	0.96	0.96	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	54.35	54.35	54.35	205
19	Traction Machine Operating Mass	[kg]	m_{TM}	2880	4205	2880	15830
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138	138	138	116
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	16000	16000	16000	3000
22	Traction Machine Front Tire Type	[--]	[--]	Radial Ply	Radial Ply	Radial Ply	Radial Ply
23	Traction Machine Front Tire Configureation	[--]	[--]	1	1	1	1
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	280	280	280	600
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	238	238	238	390
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	1111	1111	1111	1745.2
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	45.22	45.22	45.22	74.1
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	1682	1682	1682	9498
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200	1200	1200	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Radial Ply	Radial Ply	Radial Ply	Radial Ply
31	Traction Machine Rear Tire Configureation	[--]	[--]	1	1	1	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	420	420	420	420
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	357	357	357	357
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	1476	1476	1476	1374.4
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	67.83	67.83	67.83	67.83
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	2523	2523	2523	6332
37							
38	Implement Mass	[kg]	m_{imp}	4333	1324.5	1200	0
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	129	129	133	0
40	Implement Estimated Life	[h]	$t_{life,imp}$	1200	1500	1500	0
41	Implement Rated Working Width	[m]	w	3.81	7.62	3.048	3.048
42	Implement Electrical Current	[A]	i	0	0	0	0
43	Implement Electrical Voltage	[V]	V	0	0	0	0
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0	0	0	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0	0	0	0
46	Implement Rotary Operation Machine	[--]	[--]	None	None	None	Combine, corn
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0	0	0	15.5
48	Implement Type	[--]	[--]	Other Seeding	None	Row Crop Planter	None
49	Implement	[--]	[--]	Nitrogen Applicator	None	No-till, Seeding only - 1 fluted coulter/row	None
50	Implement Width Units	[--]	[--]				
51	Implement Width	[--]	w_{imp}	5	0	4	0
52	Implement Tillage Depth	[cm]	T_{depth}	1	0	1	0
53	Soil Texture Type	[--]	[--]	Medium	Medium	Medium	Medium
54							
55	Planting Rate	[seed/ha]	r_{plant}	0	0	82780	0
56	Planting Material Density	[seed/kg]	ρ_{plant}	0	0	5000	0
57	Planting Energy Content	[MJ/kg]	e_{plant}	0	0	104	0
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	50	0	0	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	78	0	0	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0	0.2	0	0
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	0	85	0	0
62							
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2	41.2	41.2	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46	46	46	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2	2.2	2.2	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	24	24	24	24
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	12	12	12	12
68							
69	Charging Station Efficiency	[--]	η_{cs}	0.95	0.95	0.95	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95	0.95	0.95	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8	0.8	0.8	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7	0.7	0.7	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$				
74	Electric Charge Time	[h]	$t_{elec,charge}$				
75							
76	Fuel Price	[$/L]	p_{fuel}	0.67	0.67	0.67	0.67
77	Lubrication Price	[$/L]	p_{lube}	6.35	6.35	6.35	6.35
78	Electricity Price	[$/kW·h]	p_{elec}	0.13	0.13	0.13	0.13
79	Traction Machine Price	[$]	p_{TM}	51590.00	51590.00	51590.00	350000.00
80	Implement Price	[$]	p_{imp}	25000.00	8100.00	23820.00	0.00
81	Planting Material Price	[$/kg]	p_{plant}	17.00	17.00	17.00	17.00
82	Fertilizer Price	[$/kg]	p_{fert}	0.78	0.78	0.78	0.78
83	Pesticide Price	[$/kg]	p_{pest}	16.50	16.50	16.50	16.50
84	Labor Wage	[$/h]	p_{labor}	15.00	15.00	15.00	15.00

A.4 Individual Task - Spraying - Utility AAV

	A	B	C	D
3	**Name**	**Units**	**Symbol**	**Herbicide**
4	Machine Type	[--]	[--]	Autonomous
5	No. of Machines	[--]	$n_{machines}$	1
6	Machines per Operator	[--]	n_{MpO}	1
7	Soil/Ground Condition	[--]	[--]	Firm
8	Field Area	[ha]	a	300
9	Operation Type	[--]	[--]	Miscellaneous
10	Operation	[--]	[--]	Boom-type sprayer
11	Field Efficiency	[--]	E_f	0.65
12				
13	Traction Machine Power Source	[--]	[--]	Electric
14	Traction Machine Drive Type	[--]	[--]	2WD
15	Traction Machine Operating Speed	[km/h]	s	5
16	Traction Machine Engine Throttle Ratio	[--]	N	0.5
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	4.6
19	Traction Machine Operating Mass	[kg]	m_{TM}	900
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	3000
22	Traction Machine Front Tire Type	[--]	[--]	Bias Ply
23	Traction Machine Front Tire Configureation	[--]	[--]	1
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	214
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	153
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	559
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	29.07
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	450
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Bias Ply
31	Traction Machine Rear Tire Configureation	[--]	[--]	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	305
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	178
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	610
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	34
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	450
37				
38	Implement Mass	[kg]	m_{imp}	0
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	0
40	Implement Estimated Life	[h]	$t_{life,imp}$	0
41	Implement Rated Working Width	[m]	w	5.5
42	Implement Electrical Current	[A]	i	10
43	Implement Electrical Voltage	[V]	V	48
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0
46	Implement Rotary Operation Machine	[--]	[--]	None
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0
48	Implement Type	[--]	[--]	None
49	Implement	[--]	[--]	None
50	Implement Width Units	[--]	[--]	
51	Implement Width	[--]	w_{imp}	0
52	Implement Tillage Depth	[cm]	T_{depth}	0
53	Soil Texture Type	[--]	[--]	Medium
54				
55	Planting Rate	[seed/ha]	r_{plant}	0
56	Planting Material Density	[seed/kg]	ρ_{plant}	0
57	Planting Energy Content	[MJ/kg]	e_{plant}	0
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0.2
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	85
62				
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	24
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	12
68				
69	Charging Station Efficiency	[--]	η_{cs}	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$	8
74	Electric Charge Time	[h]	$t_{elec,charge}$	12
75				
76	Fuel Price	[$/L]	p_{fuel}	0.67
77	Lubrication Price	[$/L]	p_{lube}	6.35
78	Electricity Price	[$/kW·h]	p_{elec}	0.13
79	Traction Machine Price	[$]	p_{TM}	15800.00
80	Implement Price	[$]	p_{imp}	0.00
81	Planting Material Price	[$/kg]	p_{plant}	17.00
82	Fertilizer Price	[$/kg]	p_{fert}	0.78
83	Pesticide Price	[$/kg]	p_{pest}	16.50
84	Labor Wage	[$/h]	p_{labor}	15.00

A.5 Individual Task - Spraying - Single-row AAV

	A	B	C	D
3	**Name**	**Units**	**Symbol**	**Herbicide**
4	Machine Type	[--]	[--]	Autonomous
5	No. of Machines	[--]	$n_{machines}$	1
6	Machines per Operator	[--]	n_{MpO}	1
7	Soil/Ground Condition	[--]	[--]	Firm
8	Field Area	[ha]	a	300
9	Operation Type	[--]	[--]	Miscellaneous
10	Operation	[--]	[--]	Boom-type sprayer
11	Field Efficiency	[--]	E_f	0.65
12				
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel
14	Traction Machine Drive Type	[--]	[--]	4WD
15	Traction Machine Operating Speed	[km/h]	s	6.437
16	Traction Machine Engine Throttle Ratio	[--]	N	0.5
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	10
19	Traction Machine Operating Mass	[kg]	m_{TM}	544
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	3000
22	Traction Machine Front Tire Type	[--]	[--]	Radial Ply
23	Traction Machine Front Tire Configureation	[--]	[--]	1
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	165
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	107.25
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	570.1
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	20.4
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	217.6
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Radial Ply
31	Traction Machine Rear Tire Configureation	[--]	[--]	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	165
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	107.25
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	570.1
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	20.4
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	326.4
37				
38	Implement Mass	[kg]	m_{imp}	
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	
40	Implement Estimated Life	[h]	$t_{life,imp}$	
41	Implement Rated Working Width	[m]	w	1.524
42	Implement Electrical Current	[A]	i	10
43	Implement Electrical Voltage	[V]	V	48
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0
46	Implement Rotary Operation Machine	[--]	[--]	None
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0
48	Implement Type	[--]	[--]	None
49	Implement	[--]	[--]	None
50	Implement Width Units	[--]	[--]	
51	Implement Width	[--]	w_{imp}	0
52	Implement Tillage Depth	[cm]	T_{depth}	0
53	Soil Texture Type	[--]	[--]	Medium
54				
55	Planting Rate	[seed/ha]	r_{plant}	0
56	Planting Material Density	[seed/kg]	ρ_{plant}	0
57	Planting Energy Content	[MJ/kg]	e_{plant}	0
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0.2
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	85
62				
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	24
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	12
68				
69	Charging Station Efficiency	[--]	η_{cs}	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$	
74	Electric Charge Time	[h]	$t_{elec,charge}$	
75				
76	Fuel Price	[\$/L]	p_{fuel}	0.67
77	Lubrication Price	[\$/L]	p_{lube}	6.35
78	Electricity Price	[\$/kW·h]	p_{elec}	0.13
79	Traction Machine Price	[\$]	p_{TM}	10000.00
80	Implement Price	[\$]	p_{imp}	0.00
81	Planting Material Price	[\$/kg]	p_{plant}	17.00
82	Fertilizer Price	[\$/kg]	p_{fert}	0.78
83	Pesticide Price	[\$/kg]	p_{pest}	16.50
84	Labor Wage	[\$/h]	p_{labor}	15.00

A.6 Individual Task - Planting - Utility AAV

	A	B	C	D
3	**Name**	**Units**	**Symbol**	**Planting**
4	Machine Type	[--]	[--]	Autonomous
5	No. of Machines	[--]	$n_{machines}$	1
6	Machines per Operator	[--]	n_{MpO}	1
7	Soil/Ground Condition	[--]	[--]	Firm
8	Field Area	[ha]	a	300
9	Operation Type	[--]	[--]	Planting
10	Operation	[--]	[--]	Row crop planter
11	Field Efficiency	[--]	E_f	0.65
12				
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel
14	Traction Machine Drive Type	[--]	[--]	MFWD
15	Traction Machine Operating Speed	[km/h]	s	8
16	Traction Machine Engine Throttle Ratio	[--]	N	0.75
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	18.1
19	Traction Machine Operating Mass	[kg]	m_{TM}	1100
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	16000
22	Traction Machine Front Tire Type	[--]	[--]	Radial Ply
23	Traction Machine Front Tire Configureation	[--]	[--]	1
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	185
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	157.25
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	749.3
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	29.8775
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	440
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Radial Ply
31	Traction Machine Rear Tire Configureation	[--]	[--]	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	280
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	238
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	1085.6
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	45.22
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	660
37				
38	Implement Mass	[kg]	m_{imp}	750
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	133
40	Implement Estimated Life	[h]	$t_{life,imp}$	1500
41	Implement Rated Working Width	[m]	w	1.524
42	Implement Electrical Current	[A]	i	0
43	Implement Electrical Voltage	[V]	V	0
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0
46	Implement Rotary Operation Machine	[--]	[--]	None
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0
48	Implement Type	[--]	[--]	Row Crop Planter
49	Implement	[--]	[--]	Seeding only - 1 fluted coul
50	Implement Width Units	[--]	[--]	
51	Implement Width	[--]	w_{imp}	4
52	Implement Tillage Depth	[cm]	T_{depth}	1
53	Soil Texture Type	[--]	[--]	Medium
54				
55	Planting Rate	[seed/ha]	r_{plant}	82780
56	Planting Material Density	[seed/kg]	ρ_{plant}	5000
57	Planting Energy Content	[MJ/kg]	e_{plant}	104
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	0
62				
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	24
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	12
68				
69	Charging Station Efficiency	[--]	η_{cs}	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$	
74	Electric Charge Time	[h]	$t_{elec,charge}$	
75				
76	Fuel Price	[$/L]	p_{fuel}	0.67
77	Lubrication Price	[$/L]	p_{lube}	6.35
78	Electricity Price	[$/kW·h]	p_{elec}	0.13
79	Traction Machine Price	[$]	p_{TM}	17234.80
80	Implement Price	[$]	p_{imp}	12000.00
81	Planting Material Price	[$/kg]	p_{plant}	17.00
82	Fertilizer Price	[$/kg]	p_{fert}	0.78
83	Pesticide Price	[$/kg]	p_{pest}	16.50
84	Labor Wage	[$/h]	p_{labor}	15.00

A.7 Individual Task - Planting - Single-row AAV

	A	B	C	D
3	**Name**	**Units**	**Symbol**	**Planting**
4	Machine Type	[--]	[--]	Autonomous
5	No. of Machines	[--]	$n_{machines}$	1
6	Machines per Operator	[--]	n_{MpO}	1
7	Soil/Ground Condition	[--]	[--]	Firm
8	Field Area	[ha]	a	300
9	Operation Type	[--]	[--]	Planting
10	Operation	[--]	[--]	Row crop planter
11	Field Efficiency	[--]	E_f	0.65
12				
13	Traction Machine Power Source	[--]	[--]	Electric
14	Traction Machine Drive Type	[--]	[--]	4WD
15	Traction Machine Operating Speed	[km/h]	s	2.02
16	Traction Machine Engine Throttle Ratio	[--]	N	1
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96
18	Traction Machine Rated Power	[kW]	P_{rated}	0.4
19	Traction Machine Operating Mass	[kg]	m_{TM}	65
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	3000
22	Traction Machine Front Tire Type	[--]	[--]	Radial
23	Traction Machine Front Tire Configureation	[--]	[--]	1
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	152.4
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	114.3
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	381
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	11.43
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	32.5
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200
30	Traction Machine Rear Tire Type	[--]	[--]	Radial
31	Traction Machine Rear Tire Configureation	[--]	[--]	1
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	152.4
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	114.3
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	381
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	11.43
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	32.5
37				
38	Implement Mass	[kg]	m_{imp}	0
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	0
40	Implement Estimated Life	[h]	$t_{life,imp}$	0
41	Implement Rated Working Width	[m]	w	0.762
42	Implement Electrical Current	[A]	i	10
43	Implement Electrical Voltage	[V]	V	48
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0
46	Implement Rotary Operation Machine	[--]	[--]	None
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0
48	Implement Type	[--]	[--]	None
49	Implement	[--]	[--]	None
50	Implement Width Units	[--]	[--]	
51	Implement Width	[--]	w_{imp}	0
52	Implement Tillage Depth	[cm]	T_{depth}	0
53	Soil Texture Type	[--]	[--]	Medium
54				
55	Planting Rate	[seed/ha]	r_{plant}	82780
56	Planting Material Density	[seed/kg]	ρ_{plant}	5000
57	Planting Energy Content	[MJ/kg]	e_{plant}	104
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	0
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	0
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0
61	Pesticide Energy Content	[MJ/kg]	e_{pest}	0
62				
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	41.2
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	46
65	Labor Energy Rate	[MJ/h]	r_{labor}	2.2
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	24
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	12
68				
69	Charging Station Efficiency	[--]	η_{cs}	0.95
70	Efficiency of Battery	[--]	η_{ch}	0.95
71	Motor Controller Efficiency	[--]	η_{mc}	0.8
72	Electric Motor Efficiency	[--]	η_{em}	0.7
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$	2.5
74	Electric Charge Time	[h]	$t_{elec,charge}$	0.5
75				
76	Fuel Price	[$/L]	p_{fuel}	0.67
77	Lubrication Price	[$/L]	p_{lube}	6.35
78	Electricity Price	[$/kW·h]	p_{elec}	0.13
79	Traction Machine Price	[$]	p_{TM}	6900.00
80	Implement Price	[$]	p_{imp}	0.00
81	Planting Material Price	[$/kg]	p_{plant}	17.00
82	Fertilizer Price	[$/kg]	p_{fert}	0.78
83	Pesticide Price	[$/kg]	p_{pest}	16.50
84	Labor Wage	[$/h]	p_{labor}	15.00

B. MICROSOFT EXCEL MODELING TOOL

B.1 'Inputs' Sheet

	A	B	C	D	E	F
1	Launch Modeling Tool GUI					
2						
3	**Name**	**Units**	**Symbol**	***[Data Set Name]***	**Comment**	**Source**
4		[--]	[--]	Conventional	Conventional, Autonomous, Autonomous Swarm	
5	No. of Machines	[--]	$n_{machines}$	1	Number of machines	
6	Machines per Operator	[--]	n_{MpO}	1	Number of machines per operator. 1 for conventional	
7	Soil/Ground Condition	[--]	[--]	Firm	Concrete, Firm, Tilled, Soft	[3] section 3.1 figure 1
8	Field Area	[ha]	a	300		
9	Operation Type	[--]	[--]	Miscellaneous		
10	Operation	[--]	[--]	Liquid Fertilizer Applicator		
11	Field Efficiency	[--]	E_f	0.65	How efficient at time in field. Recommended value:	[1] pg 5, [3] section 5
12						
13	Traction Machine Power Source	[--]	[--]	Fossil Fuel	Fossil Fuel or Electric	
14	Traction Machine Drive Type	[--]	[--]	MFWD	2WD, MFWD, 4WD	[3] section 3.1 figure 1
15	Traction Machine Operating Speed	[km/h]	s	10.5	Speed of traction machine	Industry standards for each operation, [1] pg 5
16	Traction Machine Engine Throttle Ratio	[--]	N	0.8	Ratio of partial throttle engine speed to full throttle engine speed at operating load	[3] section 3.3.3
17	Traction Machine Mechanical Efficiency	[--]	E_m	0.96	Mechanical efficiciency of the transmission and power train	[2] section 4.2
18	Traction Machine Rated Power	[kW]	P_{rated}	187	for ICE: rated PTO power; for electric: rated motor power	
19	Traction Machine Operating Mass	[kg]	m_{TM}	11678		
20	Traction Machine Embodied Energy	[MJ/kg]	$e_{emb,TM}$	138	Energy sequestered in machine	
21	Traction Machine Estimated Life	[h]	$t_{life,TM}$	16000		[3], table 3
22	Traction Machine Front Tire Type	[--]	[--]	Radial Ply	Bias Ply, Radial Ply	[4], pg 370
23	Traction Machine Front Tire Configureation	[--]	[--]	1	1 = singles, 2 = duals	
24	Traction Machine Front Tire Section Width	[mm]	$b_{TM,f}$	480	Width of tire	[4], pg 370
25	Traction Machine Front Tire Section Height	[mm]	$h_{TM,f}$	336	Height of undeflected section; equals section width×aspect ratio	[4], pg 370
26	Traction Machine Front Tire Overall Diameter	[mm]	$d_{TM,f}$	1434	Undeflected overall tire diamter; equals rim diameter + 2×section height	[4], pg 370
27	Traction Machine Front Tire Deflection	[mm]	$\delta_{TM,f}$	63.84	Typically equals 0.19×section height	[4], pg 370
28	Traction Machine Front Static Load on Axle	[kg]	$m_{TM,f}$	4831	Determined by traction machine CG	
29	Traction Machine Front Cone Index of Soil	[kN/m²]	CI_f	1200	Note: the CI for the rear tires will be different due to compaction	[3] section 4.2.1
30	Traction Machine Rear Tire Type	[--]	[--]	Radial Ply	Bias Ply, Radial Ply	[4], pg 370
31	Traction Machine Rear Tire Configureation	[--]	[--]	2	1 = singles, 2 = duals	
32	Traction Machine Rear Tire Section Width	[mm]	$b_{TM,r}$	480	Width of tire	[4], pg 370
33	Traction Machine Rear Tire Section Height	[mm]	$h_{TM,r}$	384	Height of undeflected section; equals section width×aspect ratio	[4], pg 370
34	Traction Machine Rear Tire Overall Diameter	[mm]	$d_{TM,r}$	1936.4	Undeflected overall tire diamter; equals rim diameter + 2×section height	[4], pg 370
35	Traction Machine Rear Tire Deflection	[mm]	$\delta_{TM,r}$	72.96	Equals 0.19×section height	[4], pg 370
36	Traction Machine Rear Static Load on Axle	[kg]	$m_{TM,r}$	6847	Determined by traction machine CG	
37						
38	Implement Mass	[kg]	m_{imp}	8820		
39	Implement Embodied Energy	[MJ/kg]	$e_{emb,imp}$	129	Energy sequestered in impliment	
40	Implement Estimated Life	[h]	$t_{life,imp}$	1200		
41	Implement Rated Working Width	[m]	w	11.43	Also called effective width	
42	Implement Electrical Current	[A]	i	0	How much current the implement consumes	
43	Implement Electrical Voltage	[V]	V	0	How much voltage the implement requires	
44	Implement Hydraulic Fluid Flow	[L/min]	Q	0	Fluid flow rate required by implement	
45	Implement Hydraulic Pressure Drop	[kPa]	Δp	0	Fluid pressure drop required by implement	
46	Implement Rotary Operation Machine	[--]	[--]	None		
47	Implement Material Feed Rate	[t/h wb]	F_{mat}	0		
48	Implement Type	[--]	[--]	Other Seeding		
49	Implement	[--]	[--]	Nitrogen Applicator		
50	Implement Width Units	[--]	[--]			
51	Implement Width	[--]	w_{imp}	15	NOTE: Units are automatically updated. Implement width, number of rows or tools.	[3] section 4.1.1
52	Implement Tillage Depth	[cm]	T_{depth}	1	Tillage depth for major tools, set to 1 for minor tillage tools and seeding implements	[3] section 4.1.1
53	Soil Texture Type	[--]	[--]	Medium	Fine (high clay content), Medium (loamy soils), Coarse (sandy soils)	[3] section 4.1.1
54				0		
55	Planting Rate	[seed/ha]	r_{plant}	0	Single machine planting material deposition rate (seed, rhizome, etc.)	
56	Planting Material Density	[seed/kg]	ρ_{plant}	0		
57	Planting Energy Content	[MJ/kg]	e_{plant}	100	Energy content of planting material (seed, rhizome, etc.)	
58	Fertilizer Application Rate	[kg/ha]	r_{fert}	78	Single machine fertilizer application rate of active ingredient	
59	Fertilizer Energy Content	[MJ/kg]	e_{fert}	0	Energy content of fertilizer active ingredient	
60	Pesticide Application Rate	[kg/ha]	r_{pest}	0	Single machine pesticide application rate of active ingredient	
61	Pesticide Energy Content	[MJ/kg]	e_{pest}		Energy content of pesticide active ingredient	
62				41.2		
63	Energy Density of Fuel	[MJ/L]	u_{fuel}	46	Energy content of traction machine fuel	
64	Energy Density of Lubricant	[MJ/L]	u_{lube}	2.2	Energy content of traction machine lubrication	
65	Labor Energy Rate	[MJ/h]	r_{labor}	16	A value of 2.2 MJ/h follows the dietary energy consumption method	
66	Length of Machine Work Day	[h/work day]	$t_{work,mach}$	16		
67	Length of Human Work Day	[h/work day]	$t_{work,human}$	0.95		
68				0.95		
69	Charging Station Efficiency	[--]	η_{cs}	0.8	Efficiency of transforming grid power to charging power	
70	Efficiency of Battery	[--]	η_{ch}	0.7	Ratio of energy charged into battery to energy discharged from battery	
71	Motor Controller Efficiency	[--]	η_{mc}			
72	Electric Motor Efficiency	[--]	η_{em}			
73	Elec. Continuous Op. Time	[h]	$t_{elec,op}$			
74	Electric Charge Time	[h]	$t_{elec,charge}$	0.665713886		
75				6.35		
76	Fuel Price	[$/L]	p_{fuel}	0.13		
77	Lubrication Price	[$/L]	p_{lube}	300000		
78	Electricity Price	[$/kW·h]	p_{elec}	50000		
79	Traction Machine Price	[$]	p_{TM}	17		
80	Implement Price	[$]	p_{imp}	0.78		[1] Farm Power & Machinery Management, 11 ed.
81	Planting Material Price	[$/kg]	p_{plant}	16.5		[2] ASAE EP496.3 FEB2006 (R2015) Cor.1
82	Fertilizer Price	[$/kg]	p_{fert}	15	Price of fertilizer active ingredient	[3] ASAE D497.7 MAR2011 (R2015)
83	Pesticide Price	[$/kg]	p_{pest}		Price of pesticide active ingredient	[4] Off-Road Vehicle Engineering Principles
84	Labor Wage	[$/h]	p_{labor}			[5] Brixius 1987

B.2 'Outputs' Sheet

	A	B	C	D	E	F
1			**Machine Type:**	Conventional		
2	Launch Modeling Tool GUI		**No. of Machines:**	1		
3			**Operation:**	Liquid Fertilizer Applicator		
4						
5	**Name**	**Units**	**Symbol**	***[Data Set Name]***	**Comment**	**Source**
6	Tractive Efficiency	[--]	E_t	0.76	Tractive condition; depends on tractor drive type and soil/ground condition	[3] section 3.1 figure 1, [2] section 4.2
7	Rotary Power Parameter a	[kW]	a_{pto}	0	Machine specific parameter. For calculating rotary operation PTO power requirement	[3] Table 2, [2] section 4.1.2
8	Rotary Power Parameter b	[kW/m]	b_{pto}	0	Machine specific parameter. For calculating rotary operation PTO power requirement	[3] Table 2, [2] section 4.1.2
9	Rotary Power Parameter c	[kW·h/t]	c_{pto}	0	Machine specific parameter. For calculating rotary operation PTO power requirement	[3] Table 2, [2] section 4.1.2
10	Soil Parameter	[--]	F_i	0.96	Depends on implement soil texture type (i.e. F_1, F_2, F_3)	[3] Table 1, section 4.1.1
11	Machine Parameter A	[--]	A_{imp}	1800	Machine specific parameter. For calculating implement draft	[3] Table 1, section 4.1.1
12	Machine Parameter B	[--]	B_{imp}	0	Machine specific parameter. For calculating implement draft	[3] Table 1, section 4.1.1
13	Machine Parameter C	[--]	C_{imp}	0	Machine specific parameter. For calculating implement draft	[3] Table 1, section 4.1.1
14	Field Capacity	[ha/h]	C_a	7.80	Effective field capacity	[2] section 5.2
15	Total Field Task Time	[h]	t_{field}	38.5	Time it takes to complete the desired task	
16	Implement Soil and Crop Resistance	[N]	MR_{SC}	25920.0	Total force parallel to direction of travel that is required to propel the implement	[3] section 4.1.1, [2] section 4.1.1
17	Mobility Number, Front Tire	[--]	$B_{n,f}$	33.92		[3] section 3.2.1
18	Cone Index of Soil, Rear Tire	[kN/m²]	CI_r	1252		[5]
19	Mobility Number, Rear Tire	[--]	$B_{n,r}$	77.49		[3] section 3.2.1
20	Slip	[--]	slip	0.09	Optimum slip ranges depending on soil condition	[2] section 3.3
21	Motion Resistance Ratio, Front Tire	[--]	ρ_f	0.07	Ratio of motion resistance to dynamic wheel load	[4] pg 371
22	Motion Resistance Ratio, Front Tire	[--]	ρ_r	0.05	Ratio of motion resistance to dynamic wheel load	[4] pg 371
23	Motion Resistance, Front Axle	[N]	MR_f	3164.1		[3] section 3.2.1.2
24	Motion Resistance, Rear Axle	[N]	MR_r	3306.5		[3] section 3.2.1.2
25	Traction Machine Motion Reistance	[N]	MR_{TM}	6470.6	Force required to overcome rolling resistance of the traction machine	
26	Total Draft	[N]	D_{total}	32390.6	Total force required to propel machine and implement	
27	Total Drawbar Power Req.	[kW]	P_{db}	94.5	Power required to move implement and traction machine	[2] section 4.1.13
28	Implement Rotary Power Req.	[kW]	P_{pto}	0.0	Power-takeoff power required by the implement	[2] section 4.1.2
29	Implement Hydraulic Power Req.	[kW]	P_{hyd}	0.0	Hydraulic power required by the implement	[2] section 4.1.3
30	Implement Electrical Power Req.	[kW]	P_{el}	0.0	Electric power required by the implement	[2] section 4.1.4
31	Current Op. Equiv. PTO Power Req.	[kW]	P_{op}	129.5	Equivalent total PTO power required by current operation	[2] section 4.2
32	Available PTO Power Ratio	[--]	X	0.69	Fraction of equiv PTO power available	[3] section 3.3.3
33	Partial Throttle Multiplier	[--]	PTM	0.89		[3] section 3.3.3
34	Spec. Fuel Consumption Vol.	[L/kW·h]	SFC_v	0.32		[3] section 3.3.3
35	Current Op. Fuel Consump. Rate	[L/h]	Q_{fuel}	41.2	How much fuel the current operation consumes	
36	Current Op. Lube Consumption	[L/h]	Q_{lube}	0.13	How much lubrication the current operation consumes	
37	Energy Rate of Consumed Fuel	[MJ/ha]	E_{fuel}	243		
38	Energy Rate of Consumed Lube	[MJ/ha]	E_{lube}	0.0		
39	Fossil Energy Consumption Rate	[MJ/ha]	E_{fossil}	243	Combined fuel and lubrication energy consumption rate	
40	Energy Rate of Consumed Electricity	[MJ/ha]	E_{elec}	#DIV/0!		
41	Emb. Energy Consump - Trac Mach	[MJ/ha]	$E_{emb,TM}$	13		
42	Emb. Energy Consump - Imp	[MJ/ha]	$E_{emb,imp}$	122		
43	Emb. Energy Consumption Planting	[MJ/ha]	$E_{emb,planting}$	0		
44	Emb. Energy Consumption Fertilizer	[MJ/ha]	$E_{emb,fert}$	0		
45	Emb. Energy Consumption Pesticide	[MJ/ha]	$E_{emb,pest}$	0		
46	Human Labor Time	[h]	t_{labor}	38.5	Total number of work-hours to complete task	
47	Days to Complete Task	[work day]	t_{task}	2.40		
48	Propulsion Energy Rate Consumption	[MJ/ha]	E_{prop}	243		
49	Emb. Energy Consump. - Machinery	[MJ/ha]	$E_{emb,mach}$	134		
50	Emb. Energy Consump. - Input Mat'l	[MJ/ha]	$E_{emb,matl}$	0		
51	Labor Energy Consumption	[MJ/ha]	E_{labor}	2.1		
52	Propulsion Pwr Source Cost - Fossil	[$/ha]	C_{fossil}	5077.74		
53	Propulsion Pwr Source Cost - Elec	[$/ha]	C_{elec}	#DIV/0!		
54	Propulsion Pwr Source Cost	[$/ha]	C_{prop}	5077.74		
55	Machinery Cost	[$/ha]	C_{mach}	0.00		
56	Input Material Cost	[$/ha]	C_{matl}	1170.00		
57	Labor Cost	[$/ha]	C_{labor}	0.00		
58	Total Machinery Capital Cost	[$]	$C_{total,capital}$	17.78		
59	Total Propulsion Pwr Source Cost	[$]	$C_{total,prop}$	1523323.21		
60	Total Machinery Cost	[$]	$C_{total,mach}$	0.07		
61	Total Input Material Cost	[$]	$C_{total,matl}$	351000.00		
62	Total Labor Cost	[$]	$C_{total,labor}$	0.00		
63						
64	Required Gross Fossil Fuel Power	[kW]	$P_{req,fossil}$	526		
65	Required Gross Electric Power	[kW]	$P_{req,elec}$	#DIV/0!		
66		[--]	η_{fossil}	0.25		
67		[--]	η_{elec}	#DIV/0!		
68						
69	Energy-per-field-time - propulsion	[MJ/h]		1895		
70	Energy-per-field-time - machinery	[MJ/h]		1049		
71	Energy-per-field-time - input mat'l	[MJ/h]		0		
72						
73	Cost-per-field-time - propulsion	[$/h]		39611.35		
74	cost-per-field-time - machinery	[$/h]		0.00		
75	cost-per-field-time - input matl	[$/h]		9127.14		
76	cost-per-field-time - labor	[$/h]		0.00		

B.3 'Misc Input Options' Sheet

	A	B	C
1	**Field Efficiency**		
2	Tillage	Range	Typ.
3	Moldboard plow	0.7-0.9	85
4	Heavy-duty disk	0.7-0.9	85
5	Tandem disk harrow	0.7-0.9	80
6	(Coulter) chisel plow	0.7-0.9	85
7	Field cultivator	0.7-0.9	85
8	Spring tooth harrow	0.7-0.9	85
9	Roller-packer	0.7-0.9	85
10	Mulcher-packer	0.7-0.9	80
11	Rotary hoe	0.7-0.85	80
12	Row crop cultivator	0.7-0.9	80
13	Planting		
14	Rotary tiller	0.7-0.9	85
15	Row crop planter	0.5-0.75	65
16	Grain drill	0.55-0.8	70
17	Harvesting		
18	Corn picker sheller	0.6-0.75	65
19	Combine	0.6-0.75	65
20	Combine (SP)	0.65-0.8	70
21	Mower	0.75-0.85	80
22	Mower (rotary)	0.75-0.9	80
23	Mower-conditioner	0.75-0.85	80
24	Mower-conditioner (rotary)	0.75-0.9	80
25	Windrower (SP)	0.7-0.85	80
26	Side delivery rake	0.7-0.9	80
27	Rectangular baler	0.6-0.85	75
28	Large rectangular baler	0.7-0.9	80
29	Large round baler	0.55-0.75	65
30	Forage harvester	0.6-0.85	70
31	Forage harvester (SP)	0.6-0.85	70
32	Sugar beet harvester	0.5-0.7	60
33	Potato harvester	0.55-0.7	60
34	Cotton picker (SP)	0.6-0.75	70
35	Miscellaneous		
36	Fertilizer spreader	0.6-0.8	70
37	Boom-type sprayer	0.5-0.8	65
38	Air-carrier sprayer	0.55-0.7	60
39	Bean puller-windrower	0.7-0.9	80
40	Beet topper/stalk chopper	0.7-0.9	80
41	Liquid Fertilizer Applicator	0.5-0.75	65
42	Other		

	E	F	G	H	I
1	**Tractive Condition**				
2	Type	Concrete	Firm	Tilled	Soft
3	2WD	87	72	67	55
4	MFWD	87	76	72	64
5	4WD	88	77	75	70
6	Track	88	76	74	72

	E	F	G	H
8	**Rotary Power Requirement Parameters**			
9			**Parameter**	
10	**Machine Type**	**a**	**b**	**c**
11	None	0	0	0
12	Baler, small rectangular	2	0	1.02
13	Baler, large rectangular bales	4	0	1.3
14	Baler, large round (var. chamber)	4	0	1.1
15	Baler, large round (fix. chamber)	2.5	0	1.8
16	Beet harvester	0	4.2	0
17	Beet topper	0	7.3	0
18	Combine, small grains	20	0	3.64
19	Combine, corn	35	0	1.64
20	Cotton picker	0	9.3	0
21	Cotton stripper	0	1.9	0
22	Feed mixer	0	0	2.3
23	Forage blower	0	0	0.9
24	Flail harvester, direct-cut	10	0	1.1
25	Forage harvester, corn silage	6	0	3.35
26	Forage harvester, wilted alfalfa	6	0	4.05
27	Forage harvester, direct cut	6	0	5.75
28	Forage wagon	0	0	0.3
29	Grinder mixer	0	0	4
30	Manure spreader	0	0	0.2
31	Mower, cutterbar	0	1.2	0
32	Mower, disk	0	5	0
33	Mower, flail	0	10	0
34	Mower-conditioner, cutterbar	0	4.5	0
35	Mower-conditioner, disk	0	8	0
36	Potato harvester	0	10.7	0
37	Potato windrower	0	5.1	0
38	Rake, side delivery	0	0.4	0
39	Rake, rotary	0	2	0
40	Tedder	0	1.5	0
41	Tub grinder, straw	5	0	8.4
42	Tub grinder, alfalfa hay	5	0	3.8
43	Windrower/swather, small grain	0	1.3	0

	K	L	M	N	O	P	Q	R
1	**Implements**							
2			Machine Parameters			Soil Parameters		
3		Width Units	A	B	C	F1	F2	F3
4	Major Tillage Tools					Fine	Medium	Coarse
5	Subsoiler/manure injector - narrow point	tools	226	0	1.8	1	0.7	0.45
6	Subsoiler/manure injector - 30 cm winged point	tools	294	0	2.4	1	0.7	0.45
7	Moldboard plow	m	652	0	5.1	1	0.7	0.45
8	Chisel plow - 5 cm straight point	tools	91	5.4	0	1	0.85	0.65
9	Chisel plow - 7.5 cm shovel/ 35 cm sweep	tools	107	6.3	0	1	0.85	0.65
10	Chisel plow - 10 cm twisted shovel	tools	123	7.3	0	1	0.85	0.65
11	Sweep plow - primary tillage	m	390	19	0	1	0.85	0.65
12	Sweep plow - secondary tillage	m	273	13.3	0	1	0.85	0.65
13	Disk, harrow, tandem - primary tillage	m	309	16	0	1	0.88	0.78
14	Disk, harrow, tandem - secondary tillage	m	216	11.2	0	1	0.88	0.78
15	Disk, harrow, offset - primary tillage	m	364	18.8	0	1	0.88	0.78
16	Disk, harrow, offset - secondary tillage	m	254	13.2	0	1	0.88	0.78
17	Disk, gang, single - primary tillage	m	124	6.4	0	1	0.88	0.78
18	Disk, gang, single - secondary tillage	m	86	4.5	0	1	0.88	0.78
19	Coulters - smooth or ripple	tools	55	2.7	0	1	0.88	0.78
20	Coulters - bubble or flute	tools	66	3.3	0	1	0.88	0.78
21	Field cultivator - primary tillage	tools	46	2.8	0	1	0.85	0.65
22	Field cultivator - secondary tillage	tools	32	1.9	0	1	0.85	0.65
23	Row crop cultivator - S-tine	rows	140	7	0	1	0.85	0.65
24	Row crop cultivator - C-shank	rows	260	13	0	1	0.85	0.65
25	Row crop cultivator - no-till	rows	435	21.8	0	1	0.85	0.65
26	Rod weeder	m	210	10.7	0	1	0.85	0.65
27	Disk-bedder	rows	185	9.5	0	1	0.85	0.78
28	Minor Tillage Tools							
29	Rotary hoe	m	600	0	0	1	1	1
30	Coil tine harrow	m	250	0	0	1	1	1
31	Spike tooth harrow	m	600	0	0	1	1	1
32	Spring tooth harrow	m	2000	0	0	1	1	1
33	Roller packer	m	600	0	0	1	1	1
34	Roller harrow	m	2600	0	0	1	1	1
35	Land plane	m	8000	0	0	1	1	1
36	Row Crop Planter							
37	Prepared seedbed - mounted seeding only	rows	500	0	0	1	1	1
38	Prepared seedbed - drawn seeding only	rows	900	0	0	1	1	1
39	Prepared seedbed - Seed, fertilizer, herbicides (SFH)	rows	1550	0	0	1	1	1
40	No-till, SFH - 1 fluted coulter/row	rows	1820	0	0	1	0.96	0.92
41	No-till, Seeding only - 1 fluted coulter/row	rows	670	0	0	1	0.96	0.92
42	Zone-till, SFH - 3 fluted coulters/row	rows	3400	0	0	1	0.94	0.82
43	Grain Drill							
44	w/ press wheels - <2.4 m drill width	rows	400	0	0	1	1	1
45	w/ press wheels - 2.4 to 3.7 m drill width	rows	300	0	0	1	1	1
46	w/ press wheels - >3.7 m drill width	rows	200	0	0	1	1	1
47	No-till - 1 fluted coulter/row	rows	720	0	0	1	0.92	0.79
48	Other Seeding							
49	Hoe drill - primary tillage	m	6100	0	0	1	1	1
50	Hoe drill - secondary tillage	m	2900	0	0	1	1	1
51	Pneumatic drill	m	3700	0	0	1	1	1
52	Nitrogen Applicator	rows	1800	0	0	1	0.96	0.92
53	None							
54	None		0	0	0	0	0	0

B.4 'Help Tip Text' Sheet

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Operation Tab**		**Field Tab**		**Traction Machine Tab**		**Traction Machine Axles Tab**		**Implement Tab**		**Input Materials**		**Labor**
2	Machine Type: Conventional - typical machines, powered mostly by fossil fuels, directly operated by humans Autonomous - robotic machines operating without direct human intervention and control Autonomous Swarm - fleet of robotic machines operating in groups to maximize field coverage		Soil/Ground Condition: Common cone index (CI) values: - Hard/Concrete: > 1800 kPa - Firm: 1200 kPa - Tilled: 900 kPa - Soft: 450 kPa		Throttle Setting: Ratio of partial throttle engine speed to full throttle engine speed at operating load		Tire Section Height: Height of undeflected section. Equals [section width] × [aspect ratio]		Embodied Energy: The amount of energy sequestered in the implement. Common values: - Plow: 180 MJ/kg - Disc harrow: 149 MJ/kg - Planter: 133 MJ/kg - Fertilizer: 129 MJ/kg - Rotary hoe: 148 MJ/kg		Planting Rate: Planting material deposition rate (seed, rhizome, etc.)		Machines Per Operator: Number of machines per operator. 1 for Conventional
3	Number of Machines: Number of machines operating in 'Autonomous Swarm' Automatically set to '1' for 'Conventional' or 'Autonomous' machine type		Field Efficiency: Measure of how efficient machine time is spent effectively operating in the field. Typical field efficiency for this operation has been auto-filled.		Mechanical Efficiency: Mechanical efficiciency of the transmission and power train. Typically 96% for tractors with gear transmissions		Tire Overall Diameter: Undeflected overall tire diameter. Equals [rim diamter] + 2 × [section height]		Estimated Life: The useful service life of an implement before it becomes unprofitable for its original purpose due to obsolescence or wear		Planting Energy Content: Energy content of planting material (seed, rhizome, etc.)		Operator Efficiency: Actual labor hours exceed field machine time because of travel, lubricate, service, etc. 80-90% is a common value for conventional agricultural operations.
4	Machine Overlap: When using an autonomous swarm, how much does each machine overlap with other machines.		Cone Index of Front Tires: Common cone index (CI) values: - Hard/Concrete: > 1800 kPa - Firm: 1200 kPa - Tilled: 900 kPa - Soft: 450 kPa		Rated Power: Typical ICE: rated PTO power Electric: rated motor power		Tire Deflection: Typically 0.19 × [section height]		Rated Working Width: Also referred to as effective width				
5					Operating Weight: Total weight of traction machine; including operator, ballast, fuel, etc.				Electrical Current: Electrical current requirement for normal operation of the implement				
6					Embodied Energy: The amount of energy sequestered in the machine. Common values: - Tractor: 138 MJ/kg - Combine: 116 MJ/kg				Electrical Voltage: Electrical voltage requirement for normal operation of the implement				
7					Estimated Life: The useful service life of a machine before it becomes unprofitable for its original purpose due to obsolescence or wear				Hydraulic Flow: Fluid flow rate requirement for normal operation of the implement				
8									Hydraulic Pressure: Fluid pressure drop requirement for normal operation of the implement				
9									Material Feed Rate: Feed rate of rotary operation; reported in t/h wet basis				
10									Impliment Width: Width of implement in terms of [m], [rows], or [tools]. Units are automatically chosen based on selections made above.				
11									Operation Depth: Tillage depth for major tillage tools. Automatically set to 1 for other implement types				
12									Soil Texture: - Fine: high in clay content - Medium: loamy soils - Coarse: sandy soils				

VITA

VITA

Gabriel Wilfong

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EDUCATION

Purdue University, West Lafayette, IN — August 2015 – August 2019

Agricultural and Biological Engineering

- Doctor of Philosophy
- Specialization: agricultural robotics, controls, systems modeling and simulation, mechatronics
- Thesis Title: *Modeling and analysis of ground-based autonomous agricultural vehicles*
- GPA: 3.90/4.0

Purdue University, West Lafayette, IN — May 2009 – May 2011

Agricultural and Biological Engineering

- Master of Science in Engineering
- Specialization: fluid power, mechanical design, systems modeling and simulation
- Thesis Title: *Design and dynamic analysis of high speed on/off valve for digital pump/motors*
- GPA: 3.95/4.0

Purdue University, West Lafayette, IN — August 2004 – May 2009

Mechanical Engineering

- Bachelor of Science in Mechanical Engineering
- GPA: 3.46/4.0

TEACHING EXPERIENCE

Course Instructor, *Sensors & Process Control (ABE 460)* — Fall 2018

Purdue University, Agricultural and Biological Engineering

- Full responsibility for all aspects of course; enrollment of 53 undergraduate students
- Prepared and delivered all lectures; graded all assignments and exams
- Created syllabus, homework and laboratory assignments, exams, and teaching materials
- Coordinated with laboratory teaching assistants

Teaching Assistant, *Sensors & Process Control (ABE 460)* — Fall 2017

Purdue University, Agricultural and Biological Engineering

- Instructed and supervised laboratory activities; enrollment of 59 undergraduate students
- Designed and built new hands-on mixing tank control system for the six-week final lab project
- Revised lab handouts and homework assignments; graded all lab reports

Course Instructor, *Sensors & Process Control (ABE 460)* — Fall 2016

Purdue University, Agricultural and Biological Engineering

- Full responsibility for all aspects of course; enrollment of 42 undergraduate students
- Prepared and delivered all lectures; graded all exams
- Created syllabus, exams, and teaching materials
- Coordinated with laboratory and homework teaching assistants

Teaching Assistant, *Design of Electronic Systems (ABE 314)* Spring 2016
Purdue University, Agricultural and Biological Engineering

- Supervised and assisted with laboratory activities; enrollment of 56 undergraduate students
- Required course for all undergraduate Agricultural and Biological Engineering students
- Graded lab reports and coordinated with the other teaching assistants
- Assisted teams and provided feedback for 3D printing and an Arduino robot final project

Course Instructor, *Hydraulic Motion Control Systems (MET 432)* Spring 2015
Purdue University, Mechanical Engineering Technology

- Full responsibility for all aspects of course; enrollment of 12 undergraduate students
- Prepared and delivered all lectures and laboratory instruction; graded all coursework
- Created lecture notes, syllabus, homework and laboratory assignments, and exams
- Revised hands-on lab activities and assignments to streamline the course curriculum

MENTORING, OUTREACH, AND UNIVERSITY SERVICE

Capstone Design Adviser and Project Judge August 2016 – May 2019
Purdue University, Agricultural and Biological Engineering

- Provided feedback and assessment for quarterly senior design project presentations
- Technical adviser for teams and provided design reviews

Graduate Student Advisory Committee Board Member August 2017 – May 2019
Purdue University, College of Agriculture

- Guide the direction of graduate student initiatives and programs for the College of Agriculture
- Helped to select the Outstanding Graduate Mentor/Advisor for the College of Agriculture
- Participated in evaluating candidates for the Dean of College of Agriculture

Graduate Student Association: Recruitment Chair August 2017 – May 2019
Purdue University, Agricultural and Biological Engineering

- Fostered sense of community among departmental graduate students
- Connected with and hosted prospective graduate students
- Helped organize graduate research symposium

Graduate Student Mentor August 2017 – May 2018
Purdue University, Agricultural and Biological Engineering

- Provided support and guidance to incoming graduate student mentee
- Advised on academic issues, adjusting to graduate student life, involvement in departmental and social activities

Youth Educational Workshop, *National Youth Engineering Challenge* September 2017
Purdue University, Agricultural and Biological Engineering

- Educational workshop for 15 high school students to increase STEM involvement
- Instructed and guided groups of students with a hands-on fluid power excavator demonstrator
- Explained fluid power and hydraulics fundamentals in a relatable and fun way

Research Experience for Undergraduates (REU) Mentor Summer 2017
Purdue University, School of Engineering Technology

- Supported and mentored REU student for summer research project
- Assisted in development of electro-hydraulic excavator for youth education and outreach
- Provided technical guidance and feedback during weekly design meetings

ABE Safety Committee Member May 2016 – May 2019

Purdue University, Agricultural and Biological Engineering

- Monitored laboratory and workshop environment to prevent workplace hazards
- Maintained updated documentation and workshop procedure manuals
- Implemented system for approving student use of tools and processes

Youth Laboratory Instructor: Introduction to fluid power August 2009 – May 2011

Purdue University, Agricultural and Biological Engineering

- Hosted hands-on STEM workshops for middle and high school students throughout the year
- Women in Engineering: Girl Day, Juniors and Seniors Exploring Engineering at Purdue
- 4-H Round-Up and 4-H Science Workshops

AWARDS AND CERTIFICATES

Teaching Academy Graduate Teaching Award April 2019

Purdue University, Purdue Teaching Academy

- Acknowledgement for commitment to undergraduate education, dedication to Purdue students, and outstanding teaching contributions

Estes H. and Vashti L. Magoon Award for Excellence in Teaching March 2018

Purdue University, College of Engineering

- Recognition for outstanding graduate teaching assistants and instructors in each department

Hybrid Vehicle Systems Certificate May 2018

Purdue University, Mechanical Engineering

- Provides students with a framework for gaining relevant expertise in the area of advanced hybrid vehicle systems

Ross Fellowship August 2015

Purdue University, Agricultural and Biological Engineering

- Provide 4-yr funding for recruitment of outstanding PhD-track students to graduate programs

Fluid Power Education Foundation Scholarship Spring 2011

NFPA Education and Technology Foundation

- Provide funding for students pursuing fluid power technology fields of study

RESEARCH EXPERIENCE

Graduate Research Assistant August 2015 – August 2019

Purdue University, Agricultural and Biological Engineering

- Modeled energy requirements of autonomous agricultural vehicles (AAVs)
- Evaluated the incentives of AAVs, including food, labor shortage, and environmental impacts
- Analyzed efficiency metrics to determine feasibility for AAV deployment
- Developed user-friendly modeling program for decision making and deployment of AAVs

Graduate Research Assistant June 2009 – May 2011

Purdue University, Agricultural and Biological Engineering

- Implemented Matlab Simulink and Simscape to model hydraulic pump motor systems
- Designed and built experimental high speed on/off hydraulic valve for testing and verification
- Created data acquisition setup of hydraulic test bench using Matlab and dSpace
- Modeled fluid flow and flow forces of a high speed on/off valve using Ansys Fluent

INDUSTRY WORK EXPERIENCE

Product Engineer June 2011 – August 2015
Oerlikon Fairfield *Lafayette, IN*

- Designed planetary gearboxes through custom part design and component selection
- Set up, troubleshoot, and run tests on dynamometer to validate gearbox performance
- Designed testing structure to validate jackup oil rig gearboxes and components
- Managed interns by providing guidance, assigning meaningful projects, and tracking progress
- Prepared assembly work instructions and procedures for new gearboxes and wheel ends
- Created computer program to organize over 5,000 part dimensions and tolerance stack-ups
- Generated computer program to manage and release over 10,000 part numbers
- Achieved savings of over $150,000 by simplifying manufacturing process of high volume part

Test Lab Engineer Intern January 2011 – June 2011
Oerlikon Fairfield *Lafayette, IN*

- Created testing plans and schedules for gearboxes
- Drafted preliminary testing reports
- Designed and 3D modeled test fixtures and supporting structures

Design Engineer Intern May 2008 – August 2008
Advanced Power Projects *Fremont, CA*

- Completed gas turbine fuel nozzle redesign and analysis
- Designed and implemented pressure vessel to test gas turbine fuel nozzles
- Assisted in the writing and preparation of sales proposals involving gas turbine retrofits
- Collaborated in the development of a document control and organization system

PATENTS

Lumkes, J., Batdorff, M., Merrill K., Holland, M., & Wilfong, G. (2012). *Fluid control valve systems, fluid systems equipped therewith, and methods of using.* Patent No. 9,200,648

PUBLICATIONS, CONFERENCES, AND SYMPOSIUMS

1. Wilfong, G., & Lumkes, J. (2019) *Energy modeling and analysis of ground-based autonomous agricultural vehicles.* (In progress)
2. Wilfong, G., & Lumkes, J. (2019) *Design and analysis of high speed on/off poppet valves for digital pump motors.* International Journal of Fluid Power. (In progress)
3. Xiong, S., Wilfong, G., & Lumkes, J. (2019) *Components sizing and performance analysis of hydro-mechanical power split transmission applied to a wheel loader.* Energies, 12(9).
4. Xiong, S., Wilfong, G., & Lumkes, J. (2019) *Development of a novel high speed actuation mechanism using a MR fluid clutch and its application to a fluid control valve.* Journal of Intelligent Material Systems and Structures (Accepted)
5. Wilfong, G., Holland, M., & Lumkes, J. (2011) *Design and analysis of pilot operated high speed on/off valves for digital pump motors.* Proceedings of the 52nd National Conference on Fluid Power, pp 539-543. Las Vegas, NV, USA.
6. Holland, M., Wilfong, G., Merrill, K., & Lumkes, J. (2011) *Experimental evaluation of digital pump/motor operating strategies with a single-piston pump/motor.* Proceedings of the 52nd National Conference on Fluid Power, pp 13-20. Las Vegas, NV, USA.
7. Wilfong, G., Batdorff, M., & Lumkes, J. (2010) *Design and dynamic analysis of high speed on/off poppet valves for digital pump/motors.* 6th FPNI – PhD Symposium, pp 259-269. West Lafayette, IN, USA.