Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Cost analysis of autonomous battery electric field tractors in agriculture

Oscar Lagnelöv [a,*], Shweta Dhillon [b], Gunnar Larsson [a], Daniel Nilsson [a], Anders Larsolle [a], Per-Anders Hansson [a]

[a] Department of Energy and Technology, Swedish University of Agricultural Sciences, P.O Box 7032, SE-75007, Sweden
[b] Department of Chemistry, Uppsala University, P.O Box 538, SE-75237, Sweden

ARTICLE INFO

Article history:
Received 7 October 2020
Received in revised form
8 February 2021
Accepted 11 February 2021
Published online 1 March 2021

Keywords:
Agriculture
BEV
Economy
Autonomy
Timeliness
Battery ageing

Interest in the electrification of agricultural vehicles is increasing along with growing interest in autonomous vehicles. Individual technologies have been well-explored, but not their combined use and the effects on agricultural fieldwork. In this study, cost analysis was conducted based on a simulated vehicle system with 50 kW self-driving battery-electric drive (BED) tractors. The analysis included battery degradation due to cycling and the cost of inadequate machine capacity, as these factors are suspected to be problems for electric tractors. A dynamic discrete-event vehicle system model, a linear timeliness model and a one-dimensional battery cell ageing model were assumed. Costs obtained were compared with those of contemporary manned diesel-based systems. BED systems had equal or lower annual costs compared to conventional manned diesel-based systems; this was due to lower costs for fuel and maintenance, while providing adequate capacity and lower energy usage. Sensitivity analysis showed that operating costs were of greater significance than investment costs. The generally more expensive investment costs of BED systems were outweighed by the reduced operating costs for several different BED system systems. Battery degradation costs and timeliness were influential, but not sufficient to make the system uncompetitive. The synergistic effect of vehicular autonomy and BED outweighed several of the drawbacks of BED systems, such as frequent recharging, increased transport and reduced consecutive work time.

1. Introduction

Making agricultural systems autonomous can be an important component in increasing agricultural productivity, feeding the world and achieving sustainable food production (Bakken, Moore, & From, 2019; Lampridi et al., 2019). Vehicle electrification is seen as one of the main methods for reducing vehicular emissions and reliance on fossil fuels, both on and off road. Sweden aims to have its vehicle fleet independent of fossil fuel by 2030 and to have net zero CO_2 emissions by 2050,

* Corresponding author.
E-mail address: oscar.lagnelov@slu.se (O. Lagnelöv).
https://doi.org/10.1016/j.biosystemseng.2021.02.005

Nomenclature

A	Total arable area (ha)
a,b,c	Battery model parameters
A_n	Area of field n (ha)
BED	Battery electric drive
BES	Battery exchange system
BEV	Battery electric vehicle
$c_{B,cyc}$	Battery cost per eq. cycle (€)
CC	Conductive charging
CC/CV	Constant current/constant voltage
C_{AN}, C_{OW}, C_{OP}	Total annual cost, ownership cost and yearly operating cost (€ y^{-1})
C_x	Total investment/operating cost for component x (€)
c_x	Investment/operating cost for each unit of x (var.)
d	Inflation (%)
E_B	Battery energy content (kWh)
EOL	End-of-life (primary, for batteries)
E_{tot}	Total yearly energy requirement (kWh y^{-1})
EV	Electric vehicle
h	Vehicle work hours per day (h d^{-1})
i	Interest rate (%)
i_r	Real interest rate (%)
l_g	timeliness factor for grain g (kg ha^{-1} d^{-1})
MCTR	Mean cycles to replacement
MTTR	Mean time to replacement (yr)
n	Field number
N_B	Number of (additional) batteries
N_C	Number of chargers
N_{CA}	Number of additional chargers
N_{cycl}	Number of battery cycles
N_V	Number of vehicles
O_F,O_R,O_C	Fraction of time operator is required for fieldwork, road transport and charging (fraction)
P_C	Charger power (kW)
P_g	Grain price for the grain g (€ kg^{-1})
P_V	Vehicle power (kW)
R_x	Salvage value of component x (€)
S_n	Timeliness cost for field n (€ yr^{-1})
SoC	State-of-charge
T_D	Total active time (d)
t_n	Delay from optimal day for field n (d)
T_x	Economic lifetime for component x (y)
x_c	Relation between battery energy capacity and charger power (h)
Y	Yield (kg ha^{-1})
θ	State-of-charge (fraction)
θ_{EOL}	State-of-charge value at end-of-life (fraction)

with electrification listed as one of the vital tools in achieving this (The Government of Sweden, 2013).

In a previous study (Lagnelöv, Larsson, Nilsson, Larsolle, & Hansson, 2020), the technical possibility of a vehicle system utilising smaller, self-driving, battery-electric drive (BED) field tractors was explored. In terms of time required for spring and yearly operations they were found to be comparable with manned diesel vehicles and they were also better in terms of energy use. However, to achieve broad appeal and market uptake, a good understanding of the cost of the system is vital. Lagnelöv et al. (2020) provided a system model and technical system understanding but in this study the focus is on the cost of autonomous vehicles and battery electric systems. Previous research has examined the cost and utilisation of general autonomous systems (Lampridi et al., 2019; Marinoudi, Sørensen, Pearson, & Bochtis, 2019), performed cost analysis on autonomous row-crop cultivation (Goense, 2005) and analysed autonomous systems in specialist crops (Le, Ponnambalam, Gjevestad, & From, 2020; Reiser, Sehsah, Bumann, Morhard, & Griepentrog, 2019; Young, Kayacan, & Peschel, 2018). However, the cost of electric autonomous field tractor systems has not been thoroughly researched.

The possible cost to yield or quality loss due to lack of capacity in the system (i.e. lack of timeliness) and the cost and limitations of batteries have been identified as potential drawbacks for agricultural BED tractors (Caban, Vrabel, Sarkan, Zarajczyk, & Marczuk, 2018; Magalhães et al., 2017; Mocera & Soma, 2020; Moreda, Muñoz-García, & Barreiro, 2016). In cost analysis it is therefore important to include these drawbacks and their system effects.

Untimely or non-optimal operations can lead to indirect costs, due to yield losses or a decrease in crop quality. Prediction of optimal work time and the negative effects of non-optimal work time have been well studied (ASAE, 2000; Edwards, Dybro, Munkholm, & Sörensen, 2016; Gunnarsson, Spörndly, Rosenqvist, De Toro, & Hansson, 2009; Nilsson, 1976; Rotz & Harrigan, 2005; Savin, Matic-Kekic, Dedovic, Simikic, & Tomic, 2014; Witney, 1988). Witney (1988) identified untimely establishment, spraying and harvesting as the most important operations and concluded that adequate machine capacity is vital, but it is difficult to assess, partly due to the unique nature of each site and the erratic behaviour of the weather. The common approach is therefore to have overcapacity in the machine pool.

The effect of agricultural use and load cycles on electric vehicle (EV) batteries is not well analysed. The concern with the use of BED tractors in the field is that this heavy use will rapidly age the batteries and therefore make the system economically uncompetitive.

The aim of this study was to evaluate an autonomous battery electric vehicle (BEV) system for a Swedish agricultural context with regards to cost. Changes in timeliness and loss of battery capacity, and related costs, were studied specifically and included in the overall cost. The model developed in Lagnelöv et al. (2020) was used to develop basic data for the calculations, but in addition, a sensitivity analysis was made for several relevant variables, including component cost, charger power, degree of autonomy, and battery size, lifetime and cost.

2. Method

This section firstly presents the models used for battery ageing and timeliness, and then describes the economic calculations. Overall costs were calculated as a combination of annual ownership costs and operating costs, including battery and timeliness costs. The costs of ownership and operation were calculated from the inputs (number and size of vehicles, chargers etc.) or the main results from the system model (numbers of hours a driver is needed etc.). For timeliness and battery ageing, separate models were required, as shown in Fig. 1.

The discrete-event model from Lagnelöv et al. (2020) was used to simulate the analysed vehicle systems. The model simulates the machinery operations on a Swedish grain farm in the Uppsala region. To bring the farm machinery operations more in line with that commonly used in Sweden, a sow bed harrow replaced the spring tooth harrow used in Lagnelöv et al. (2020) with power use described by Lindgren, Pettersson, Hansson, and Norén (2002). The average power usage and working width are shown in Fig. 2. Additionally breakdown rates taken from ASAE (2000) were included in the simulations. The breakdown rates were the combined factors for a vehicle system with a field area of 200 ha and each breakdown was assumed to put the vehicle out of operation, leading to 12 h of downtime. The cost of repairing is included in the maintenance cost, so the only cost effect of a breakdown was a delay of operations. Due to being a less well-developed system it was assumed that the breakdown rate for the autonomous electric tractors was double that of the manned diesel tractors.

For timeliness, the model by Gunnarsson (2008) was used, which takes the delay in key operations for each field and turns it into an annual cost. For battery ageing, a one-dimensional battery cell model for NCA Li-ion batteries that connected voltage and capacity loss to the number of full use cycles was used. These results were then used in the main model to incorporate the effects of continuous degradation of the vehicle batteries. In addition, the results were used to dynamically determine the useful lifetime of the batteries before they needed replacing, which led to a cost per year or per cycle. All the costs were then summed to a total annual cost of operations.

2.1. Battery ageing

Battery ageing is a common electrochemical process that is dependent on different factors, including use pattern, depth of discharge, battery temperature, charge/discharge rate etc. (Barré et al., 2013; Uddin, Perera, Widanage, & Somerville, 2016). This often leads to EV batteries having a shorter life-spans than the vehicles they power, and this might require a change of battery before a change of vehicle. Therefore, it is important to estimate and include the effect of battery ageing in economic analysis of BEVs. For novel vehicle systems, the effect of battery ageing is important information when designing the system, especially if the work includes high-

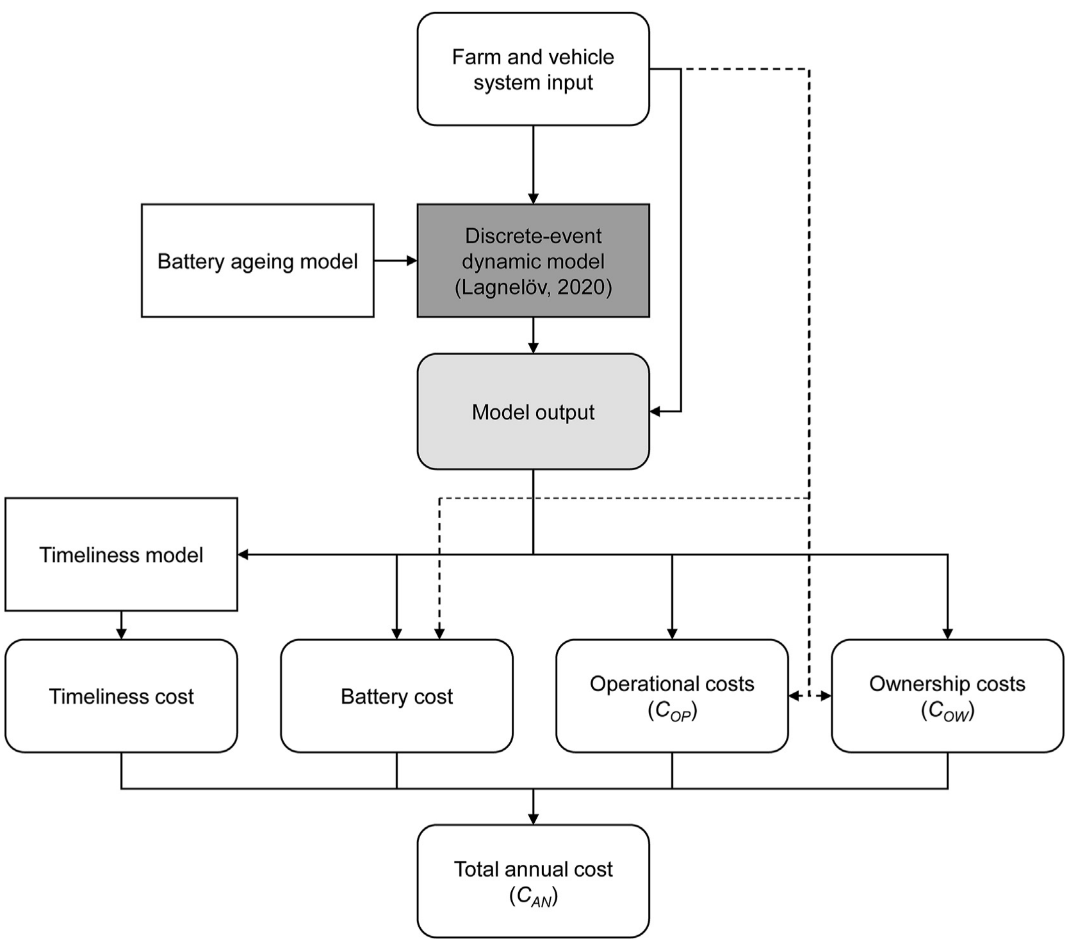

Fig. 1 – Overview of the models used (sharp-cornered boxes) and costs analysed (rounded boxes). The dotted lines indicate where system inputs were used for cost calculations.

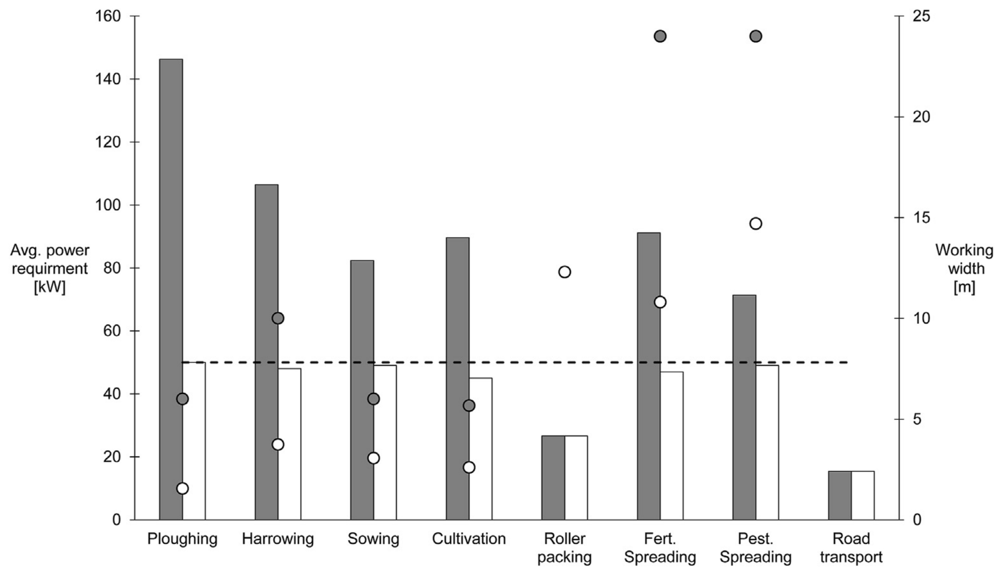

Fig. 2 – Average total power requirement (bars, left axis) and working width (circle markers, right axis) for the operations used in the simulations for the tractor sizes 250 kW (dark gray) and 50 kW (white). The maximum power of the 50 kW tractor is marked (dashed line).

power use of the battery over a longer period, as is the case in agricultural fieldwork. In this regard, the use of batteries in heavy off-road applications is different from their use in on-road personal vehicles. In this study, battery ageing was characterised as capacity of NCA batteries depending on the number of cycles for each battery and the charge rate (C-rate) of the charging station.

2.1.1. *Battery model*

A one-dimensional battery cell model was created using the 'Lithium-Ion Battery' module in COMSOL Multiphysics 5.5 (COMSOL AB, Stockholm, Sweden). In this model, graphite is used as the negative electrode (thickness 55 μm), $LiPF_6$ in 3:7 EC:EMC as electrolyte (30 μm) and NCA ($LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$) as the positive electrode (40 μm). The model was based on the porous electrode theory and concentration solution theory (Thomas, Newman, & Darling, 2002). It included ageing in the graphite electrode, where a parasitic solid electrolyte interface (SEI)-forming reaction results in irreversible loss of cyclable lithium. The kinetic expression for the SEI-forming reaction used here was based on work by Ekström and Lindberg (2015). More details regarding this model can be found in the COMSOL library (COMSOL Multiphysics, 2020). Specific simulations inputs can be found in Table A1.

2.1.2. *Model assumptions and adaptation*

Calendar ageing of the batteries was omitted, as it is less impactful for battery degradation than the number of cycles and as one of the defining characteristics of Li-ion batteries is their low capacity fade during storage (Barré et al., 2013). Ambient temperature was assumed to remain constant at 293 K and the vehicle was assumed to have a temperature control system with adequate ability to keep a constant battery temperature of 293 K during charging and discharging. The state-of-charge (SoC) is limited in the system model to stay above 20% at all times, giving a maximum depth-of-discharge interval of 20–100%, with fast charging applicable in the interval 20–80% and slower charging during the interval 80–100%. Considering field operations and type of use, it was assumed that C-rate and number of battery cycles (N_{cycl}) would be the most influential direct factors (Uddin et al., 2016; Wenzl et al., 2005).

In the model, the cycles are calculated for each battery and all batteries in operation are assumed to be used equally. The number of cycles for each battery is carried over between each year according to:

$$N_{cycl}(i) = N_{cycl}(i-1) + \frac{N_{cycl}(i)}{(N_B + N_V)} \tag{1}$$

where N_{cycl} is the number of cycles at the end of year i, N_V is the number of vehicles (as each vehicle carries one battery) and N_B is the number of spare batteries in the system.

Vehicles continue their operations even if the SoC of the batteries dips below 80%, with the batteries being replaced between working seasons. The SoC of a battery is related to the number of cycles as:

$$\theta = aN_{cycl}^3 + bN_{cycl}^2 + cN_{cycl} + d \tag{2}$$

where a, b, c and d are curve fitting parameters of the third-order polynomial curve used as a representation of the simulated values. High-order polynomials have been used to represent battery capacity fade and voltage curves by e.g. Stamps, Holland, White, and Gatzke (2005).

When the capacity fade is at $\theta = 0.8$, the battery is scheduled for replacement in the model, as this is common practice in the industry (Berg, 2015). The number of cycles this takes is denoted mean cycles to replacement (MCTR). The MCTR for each individual battery is the same, irrespective of E_B and N_B, but the mean time to replacement (MTTR) in years will change depending on the number and size of the batteries. Since the cycles were disturbed roughly evenly between the different batteries in the system, it was assumed in this study that MTTR increases with a higher number of batteries in the system and with larger batteries.

2.2. Timeliness

When studying timeliness, there is often mention of an optimum day, i.e. the day where the specific operation will produce the highest yield (Gunnarsson, 2008; Witney, 1988). In this study, the timeliness of sowing was the main focus, as the simulation model used (Lagnelöv et al., 2020) concentrates on operations performed by tractors. Of those, sowing was viewed as having the greatest impact and other operations were considered generally as being preparation for sowing.

It was assumed that the first workable day of the year was optimal for spring-based sowing and that the first day after harvesting finished in autumn was optimal for autumn sowing. This was based on the concept of delayed scheduling presented by Gunnarsson (2008), where all the time that elapses beyond the optimal day is assumed to incur a yield loss. Since harvesting was not included in the simulation, it was assumed that harvesting was carried out with adequate capacity and that no timeliness penalty was incurred.

The slope and shape of the curve displaying yield loss are different in different sources, e.g. Gunnarsson (2008) and ASAE (2000) characterised the yield loss as linear and Witney (1988) characterised it as parabolic. Here the linear method was used, with the timeliness factors taken from Gunnarsson (2008).

For each scenario, the total time elapsed from the first possible day was measured. The cost of yield loss for a specific field n (S_n, in € y^{-1}) due to non-optimal sowing date was assumed to depend linearly on the delayed scheduling described by Gunnarsson and Hansson (2004) and Gunnarsson et al. (2009).

A dynamic simulation was used to simulate many of the events described by Gunnarsson and Hansson (2004) and combine them into a single parameter for the particular field, n (see Table 1). This allowed use of the following equation, as also proposed by Nilsson (1976) and used by Gunnarsson and Hansson (2004):

$$S_n = l_g \times t_n \times p_g \times A_n \tag{3}$$

where l_g is the timeliness factor in kg ha^{-1} d^{-1} for grain g, t_n is the time delay from the optimal day in d for field n, p_g is the grain price in € kg^{-1} for grain g and A_n is the total crop area in ha for field n. The delay, t_n, was measured at the completion of each field.

The optimal day was calculated for sowing and was set as the first workable day of the year. As explained in Lagnelöv et al. (2020), in the model it is assumed that the simulation period starts with the soil saturated, due to thawing and precipitation, so it takes a period of time before the first workable day for the soil, and it is from that day that the delay is calculated.

To calculate the cost of the delay, the optimum price for grain, p_g, and the yield needed to be defined. The price of grain was taken from the agricultural wholesale dealer Lantmännen's prices for 2019, and yield was based on the normal yields given in Statistics Sweden (2019) for the Uppsala region for 2018 (Table 2). The timeliness factors proposed in Gunnarsson (2008) were used (Table 2). For some grain crops, only the factor values for organic production were available, but this was assumed to have little effect on the results.

2.3. Economic analysis

2.3.1. Cost calculation

The cost of the autonomous BED system was calculated using the total annual cost of operation (C_{AN}) and compared with the calculated cost for a diesel counterpart, and with literature values. The calculation method based on combined investment, ownership and operating costs of vehicles found in Wu, Inderbitzin, and Bening (2015) and Lampridi et al. (2019) was adapted and used, including straight-line depreciation as seen in Eq. (4). When considering the cost of an autonomous system and agricultural robotics, the methods found in Lampridi et al. (2019) and Marinoudi et al. (2019) were used.

$$C_{AN} = C_{OW} + C_{OP} \tag{4}$$

where C_{AN} is the annual cost of operations, C_{OW} is the ownership cost calculated as shown in Eq. (5) and C_{OP} is the operating cost, calculated as shown in Eq. (6). All values are in € yr^{-1}.

C_{OW} is the combined cost of investment (fixed depreciation cost and capital cost) as an equivalent annual cost with the average interest rate method used, as used by Lampridi et al. (2019):

$$C_{OW} = \sum \frac{C_x - R_x}{T_x} + \frac{(C_x - R_x)}{2} i_r \; ; [x = B,\ C,\ CA,\ BCS,\ A,\ V] \tag{5}$$

$$C_{OP} = \sum C_y ; \left[y = \begin{cases} E,\ ME,\ O\ (BED) \\ D,\ MD,\ O\ (Diesel) \end{cases} \right] \tag{6}$$

where c_x is the component investment cost in €, R_x is the salvage value in € (normally 10% of purchase price), T_x is the economic lifetime in years and C_y is the operating cost in € yr^{-1} (where x and y are the specific component subscript for the investment and operating costs respectively, described in Tables 3 and 4) and i_r is the real interest rate correction factor (Lampridi et al., 2019), calculated as shown in Eq. (7).

$$i_r = \frac{i + d}{1 + d} \tag{7}$$

where i is the interest rate and d is inflation, both in %.

Here, d was set to 2% to match Sweden's inflation goal, and i was set to 2.75%, which is a reasonable interest rate for agricultural businesses (L. Hylander (Swedbank), personal communication, June 17, 2020).

The component costs and equations for each parameter are shown in Tables 3 and 4. Sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, 2.3.7, 2.3.8 and 2.3.9 explain the costs, sources and assumptions for each category. When no data were available, it was assumed that both the BED system and the corresponding diesel tractor system had equal costs. This included vehicle housing, seeds, fertilisers, pesticides, insurance and non-field-related farming expenses. For all conversions between currencies, the following rates from May 7, 2020 were used: 1 € = 10.64 SEK = 1.10 US$.

Table 1 – Field number and area in the simulations, and type of grain grown; O = oats, W.W = winter wheat, S.W = spring wheat and B = barley.

Field no. (n)	1	2	3	4	5	6	7	8	9	10	11	12
Area (A_n) [ha]	10	16	22	13	15	26	6	14	22	28	15	13
Grain	O	W.W	B	B	S.W	O	W.W	O	S.W	W.W	B	S.W

Table 2 – Timeliness factors and yields for the grain crops assumed in simulations. Timeliness factors from (Gunnarsson, 2008) and yield data from Statistics Sweden (2019).

	Winter wheat	Spring wheat	Barley	Oats
p_g, Grain price [€ kg^{-1}]	0.130	0.130	0.118	0.143
Y_g, Yield [kg ha^{-1}]	5658	4221	4581	3823
l_g, Timeliness factor [kg ha^{-1} d^{-1}]	55	59[a]	40	23[a]
Timeliness, [% d^{-1}]	1.1	1.5	1.0	0.9

[a] Value for organic production instead of conventional.

2.3.2. Charging infrastructure

The cost of chargers included the price for the charging station, the grid connection cost, casing, site establishment, wiring, installation safety control and the cost of contract work. The total cost for this ranged from 35,000–80,000 €, according to Swedish Energy Agency (2019). The assumed cost was set to $c_C = 50{,}000$ €. It was assumed that the full cost of establishing charging infrastructure was required for the first charging station ($N_C = 1$), and that any additional charging ($N_C > 1$) just required investing in additional charging stations, which was priced at $c_{CA} = 25{,}660$ € for a Siemens mode 3 fast charger (Engström & Lagnelöv, 2018). It was assumed that the connection of charging stations were within the limit of the farms pre-existing power capacity and that no upgrade in fuse size was needed.

2.3.3. Battery changing system

An industry sector that has similar needs to the agricultural sector, and has solutions for battery replacement technology, is the forklift sector. Its solutions are less complex and costly than the large-scale systems found in mining vehicles or buses. For example, a battery storage and replacement system used for forklift trucks from the Solus Group costs 5000–10,000 €, depending on capacity and complexity (Solus Group, 2019). The higher cost ($c_{BCS} = 10{,}000$ €) was chosen here, since knowledge of the system is low.

2.3.4. Tractor prices

The cost of investing in a new field tractor was calculated using Eq. (8) which was developed by Engström and Lagnelöv (2018) and estimates the vehicle price based on the rated engine power. The equation is regression-based and uses data from Swedish tractor retailers. The equation was verified using official data on the average price of tractors in 2018 (Statistics Sweden, 2019), with acquisition values from Maskinkalkylgruppen (2020), and compared with linear relationships between price and rated power presented in Goense (2005). It was assumed that engine/motor and other driveline components were included in this price. To represent the lack of mass production for BED systems, it was

Table 3 – Costs, lifetime and equations used to calculate combined cost of investment (C_{OW}), where C (capital) is the total investment cost in € and c (lower-case) is the investment cost per component or unit in €. Sources given in sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, and 2.3.7.

Component (subscript)	Component cost (c_x)	Assumed economic lifetime (T_x) [yr]	Equation
Battery (B)	146 € kWh^{-1}	(see section 2.3.6)	$C_B = c_B E_R (N_V + N_B)$
Charger (C)	50,000 €	20	$C_C = c_C + (N_C - 1)c_{CA}$
Additional charging stations (CA)	25,662 €	20	
Battery changing system (BCS)	10,000 €	20	$C_{BCS} = c_{BCS} N_{BCS}$
Autonomy system (A)	17,446 €	15	$C_A = c_A N_V$
Tractor, $P_R = 50$ kW (V)	45,005 €	15	$C_V = \frac{N_V (8107.2 \times P_R + 10970)}{10.64}$
Tractor, $P_R = 250$ kW (V)	191,550 €	15	

Table 4 – Costs and equations used to calculate operating costs of the system (C_{OP}). Sources given in sections 2.3.2, 2.3.3, 2.3.4, 2.3.5, 2.3.6, 2.3.7, 2.3.8 and 2.3.9.

Parameter	Variable	Component cost (c_x)	Units	Yearly cost [€ yrs^{-1}]
Electricity	C_E	0.08	€ kWh^{-1}	$C_E = c_E E_{tot}$
Diesel	C_D	0.086	€ kWh^{-1}	$C_D = c_D E_{tot}$
Maintenance Diesel	C_{MD}	48.8	€ ha^{-1}	$C_{MD} = c_{MD} A$
Maintenance BED	C_{ME}	35.1	€ ha^{-1}	$C_{ME} = c_{ME} A$
Operator	C_O	28.2	€ h^{-1}	$C_O = \sum c_O\, a\, h_d$
Battery cost per cycle	$C_{B,cyc}$	(see section 2.3.6)	€ cycle^{-1}	$C_{B,cyc} = c_{B,cyc} N_y$

assumed that the BED tractors had a 15% increase in investment cost compared to Eq. (8).

$$c_T\,[€] = (8107.2 * P_R + 10970)[SEK] * \frac{1}{10.64}\,[€/SEK] \quad (8)$$

2.3.5. Autonomous systems

The system architecture and sensory requirements for autonomous systems can vary between different sectors, vehicles and levels of autonomy. There is a lack of data for autonomous systems in the agricultural sector, which necessitates use of data from other sectors. Engström and Lagnelöv (2018) used a 10,000 € template value based on the increased price of Volvo cars when equipped with autonomous capacity, which is similar to the findings of Daziano, Sarrias, and Leard (2017) for the add-on Cruise-RP1 system (Cruise, San Francisco, CA, USA), priced at 10,000 $ (~9000 €). Vedder, Vinter, and Jonsson (2018) estimated that building a vehicle with self-driving capacity was possible at prices from 2000 €. Higher estimates have been given, putting the price for full autonomous capability in cars at 70,000 $ (Fagnant, Kockelman, & Bansal, 2015). Bösch, Becker, Becker, and Axhausen (2018) assumed that for fleet-based cars, the price increase would be 20% higher for cars with autonomous systems compared with those without, a value that Brundrett (2014) found applicable for autonomous mining vehicles. The autonomous diesel-powered tractor Robotti (Agrointelli, Aarhus, Midtjylland, Denmark) is priced in range as modern manned tractors, 133,170–192.447 € depending on rated power and options (F. Rom (Agrointelli), personal communication, January 20, 2021). It was assumed that the cost for the total autonomous system of SAE level 4 or above (SAE, 2018) was 20% of the average Swedish tractor price (Statistics Sweden, 2019), which resulted in $c_A = 17{,}450$ €.

2.3.6. Batteries

In a summary by Comello and Reichelstein (2019), the market price for a Li-ion battery system in the US was projected to range between 113 and 172 € kWh^{-1} in 2020. Tsiropoulos, Tarvydas, and Lebedeva (2018) estimated a cost in the range of 170–215 € kWh^{-1} for Li-ion battery packs in the EU in 2017. This was based on predictions by Nykvist and Nilsson (2015) of a possible pack cost of 182 € kWh^{-1} in 2020. The actual cost will depend on cell chemistry, producer and production method (Tsiropoulos et al., 2018). Here, the cost, c_B, was set to 146 € kWh^{-1}, as it fitted multiple predictions, was the average price given by Comello and Reichelstein (2019) and was close to the 2019 market average of 142 € kWh^{-1} (McKerracher et al., 2020). For clarity, batteries are shown as both an investment cost and as an operating cost. Therefore it may be easier to calculate the cost per year, cycle or unit of energy stored, which is shown in Appendix B.

2.3.7. Fuel

Both electricity and diesel were considered as fuels in this study. The base price of diesel was taken from the Swedish average price for March 2020, as reported by SPBI (2020), and reworked to the current net price for the agricultural sector. Swedish agricultural businesses are exempt from VAT (25%) on diesel and are entitled to a carbon tax refund of 181.8 € m^{-3} diesel. The total pump-price of 1.32 € l^{-1} is thereby reduced to 0.87 € l^{-1}. Further conversion to price per unit of energy was made using the density (845 kg m^{-3}) and net calorific value (43.1 MJ kg^{-1}) of diesel found in Reif and Dietsche (2014) for a total price of 0.086 € kWh^{-1}. The price for electricity, 0.08 € kWh^{-1}, was taken from the official Swedish statistics for businesses with annual consumption between 20 and 500 MWh (Statistics Sweden, 2020).

2.3.8. Maintenance

The maintenance costs for agricultural tractors were taken from Pettersson and Davidsson (2009, pp. 1401–4963), who analysed the maintenance costs for Swedish field tractors in grain production on farms with 150–300 ha. This was verified with data from Olt, Traat, and Kuut (2010) for similar machines and production types. This put the maintenance costs within the range 20.5–48.8 € ha^{-1} for diesel systems, and the highest value of 48.8 € ha^{-1} was chosen for the present analysis.

For BED tractors there are less available data. Sources studying on-road vehicles give the maintenance cost reduction for BED tractors compared with diesel at 19–28% (Delucchi & Lipman, 2010; Propfe, Redelbach, Santini, & Friedrich, 2012), which puts the maintenance costs for BED tractors in the range 18.8–39.5 € ha^{-1}. A maintenance cost of 72% of that of a diesel tractor (35.1 € ha^{-1}) was chosen.

2.3.9. Driver & operators

For manned vehicles, it was assumed a driver needed to be hired. It was assumed that this driver was contracted on a per-hour basis related to the active time of the tractor, which is the sum of the time spent performing fieldwork, road transport and refuelling. For the autonomous systems, it was assumed that an operator was required to control the vehicle during more challenging operations and for general management of the system. The fraction of vehicle time assumed to need an operator was called operator factor, O. It was defined as a fraction between 0 and 1, and describes the fraction of hours that the vehicle needs to be managed by an operator for that specific task, with 0 being fully autonomous and 1 being fully monitored. Engström and Lagnelöv (2018) used a value of 0.1 for all tasks and Goense (2005) used 0.2 for field operations based on the complexity level of different field manoeuvres, but did not include road transport or refuelling. In this study, different values were set for fieldwork ($O_F = 0.2$, i.e. 20% of all fieldwork hours needed to be monitored), road transport ($O_R = 0.3$) and refuelling ($O_C = 0.1$), as they had different levels of complexity, with road transport assumed to be the most complex task.

The operator was assumed to have an hourly cost of 28.2 €, which is the rate recommended for the total cost of an experienced employee in the agricultural sector, including social benefits, taxes, vacation and 15% write-up for non-productive time (Maskinkalkylgruppen, 2020). For the manned systems, the values were verified with the normal yearly tractor use of 650 h y^{-1} from Maskinkalkylgruppen (2020), and were found to be within 10% of that value.

2.4. Simulation inputs

The vehicle system cases with the parameters shown in Table 5 were simulated and analysed, unless specifically

Table 5 – Base case simulation inputs for the battery electric drive (BED) tractor and inputs for the reference cases with one and two diesel tractors (D1, D2).

Case name	BED	D1	D2
Number of vehicles (N_V)	2	1	2
Vehicle power (P_V, kW)	50	250	250
Battery energy eq. carried (E_B, kWh)	50	1315	1315
Number of extra batteries (N_B)	2	–	–
Charging power (P_C, kW)	50	30,345[a]	30,345[a]
Number of chargers/fuel pumps (N_C)	1	1	1
Number of battery exchange stations (N_{BCS})	1	–	–
Daily working time (h, h d^{-1})	24	10	10

[a] Diesel pump with a flow of 50 L min^{-1}.

stated otherwise. They were chosen as a previous study found that BES performed slightly better and that a two-vehicle system provided adequate overall capacity for 200 ha, which was explored in Lagnelöv et al. (2020). The case D1 was chosen as being a reasonable diesel counterpart and D2 was chosen to represent a system with overcapacity.

The inputs were used in the dynamic discrete-event model of a 200 ha Swedish grain farm presented in Lagnelöv et al. (2020). The weather data for the years 2008–2018 were used in the soil water balance sub-system in the model, as the model was run for those years, so some results are 11-year averages.

3. Results

This section firstly presents the results of the simulation concerning battery ageing and timeliness, and then calculates the system cost from those results.

3.1. Battery ageing

Battery ageing due to cycling at different charging rates was simulated as described in section 2.1 and the results are shown in Fig. 3. The results for the capacity fade were fitted with third-order polynomials and were used in the model as an approximation of the capacity fade due to cycling. The polynomial constants were decided by the charging rate of the chargers, as depicted in Table 6.

The choice of charging rate for each case was determined using Eq. (9) and Eq. (10). The polynomial they represent was used as input in the main model:

$$C-\text{rate} = \begin{cases} 4C, & 2 \leq x_C \\ 1C, & 0.5 \leq x_C < 2, \\ 0.1C, & x_C < 0.5 \end{cases} \tag{9}$$

$$x_C = \frac{E_B}{P_C} \tag{10}$$

where x_c is the relationship between battery energy (E_B) and charging power (P_C) in h, and is used as a metric to decide the C-rate.

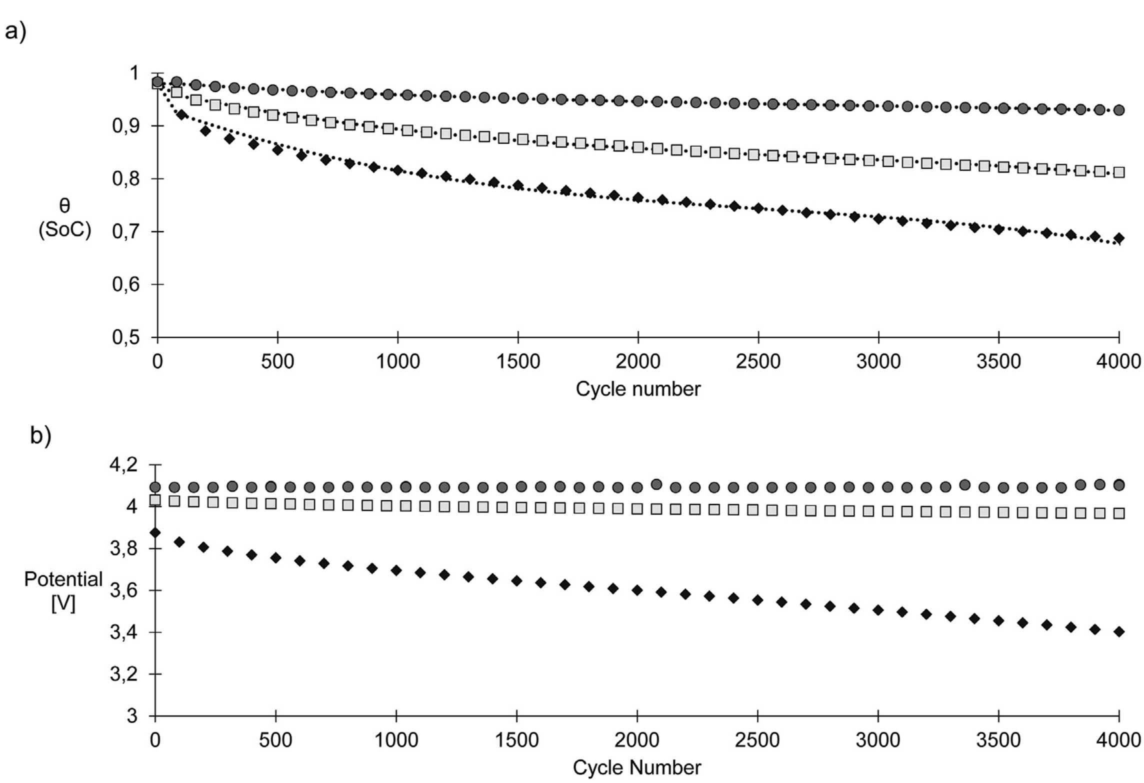

Fig. 3 – Decrease in (a) state-of-charge (SoC) and (b) voltage as a function of cycle number, simulated for three different charging rates: C/10 (circles), 1C (squares) and 4C (diamonds). Line-fitting curves from Eq. (2) (dotted lines) for the three different charging rates are shown in (a).

Table 6 – : Parameters used in Eq. (2) for different charge rates shown in Fig. 3.

C-rate	A	b	c	d	R^2
0.1C	$-8.81 * 10^{-13}$	$7.65 * 10^{-9}$	$-2.97 * 10^{-5}$	0.9820	0.997
C	$-3.37 * 10^{-12}$	$2.77 * 10^{-8}$	$-9.60 * 10^{-5}$	0.9655	0.994
4C	$-7.07 * 10^{-12}$	$5.43 * 10^{-8}$	$-1.69 * 10^{-4}$	0.9371	0.982

3.2. *Battery replacement*

A higher charging rate led to a shorter charging time and higher productivity, but it also aged the battery more rapidly than lower charging rates. This can be seen in Fig. 4, as MTTR for the given system at 4C was 2 years, while the same system had a MTTR of 7 years with 1C. For the C/10 charging rate, the chosen system did not reach the point of battery replacement in the 11 years simulated.

The limit for end-of-life (EOL) was set at 80% of starting capacity and the different charging rates reached it in differing amount of cycles: 4C reached it in 1200 cycles, 1C in 4240 cycles and C/10 in 7760 cycles.

3.3. *Timeliness*

A plot of the average delay for different vehicle systems (Fig. 5) revealed that the BED system has a longer delay in the spring than the systems with manned diesel tractors (D1 & D2). It is worth noting that the delay between fields was not insignificant, as even the best cases showed an average delay of 20 days for the highest numbered field. For autumn, none of the systems showed a long delay compared with the spring period.

The sowing interval for the BED system (Fig. 6) was within the range stated in Myrbeck (1998), with a comparable delay in the spring period to the 1-vehicle system of diesel tractors (D1) and with increased delay compared with the 2-vehicle system (D2). The autumn period sowing interval was short in all three scenarios and all systems were within the stated interval. However, since harvest was not simulated, but was simply assumed to be completed at the start of the autumn period, it is plausible that the starting date for sowing should be akin to that stated by Myrbeck (1998).

3.4. Economics

3.4.1. *Timeliness*

The delay for each grain and field in the three cases can be seen in Fig. 5. The cost for the delay for the BED case was 20,846 € in total, 18,370 € for the spring-sown crops and 2476 € for the winter wheat. The total yield loss was 30.1% compared with the optimum. For the diesel cases, the corresponding yield loss was 19.6% (D1) and 10.6% (D2), which resulted in costs of 13,569 € (D1) and 7321 € yr^{-1} (D2).

3.4.2. *Battery and energy cost*

The battery cost for the BED case, with 4 × 50 kWh NCA li-ion batteries, was 29,200 € in investment costs. The average yearly energy use was 91,462 kWh and the average number of equivalent cycles was 2464 cycles yr^{-1} (616 per battery and year). With a charging rate of 1C, the system had a theoretical MTTR of 6.8 years (7 years in simulation) and a MCTR of 4240 cycles. Using linear depreciation, this resulted in a cost of 6.8 € $cycle^{-1}$ or 0.17 € kWh^{-1}. The total energy cost (including electricity and battery cost) was then 0.97 € kWh^{-1}, compared with 0.86 € kWh^{-1} for diesel. Compared with the diesel cases, the BED system had lower energy consumption (54% of D1 and 52% of D2) and fuel costs (49–50% lower). The batteries made up 6% of the total operating costs and 14% of the investment costs for the BED case.

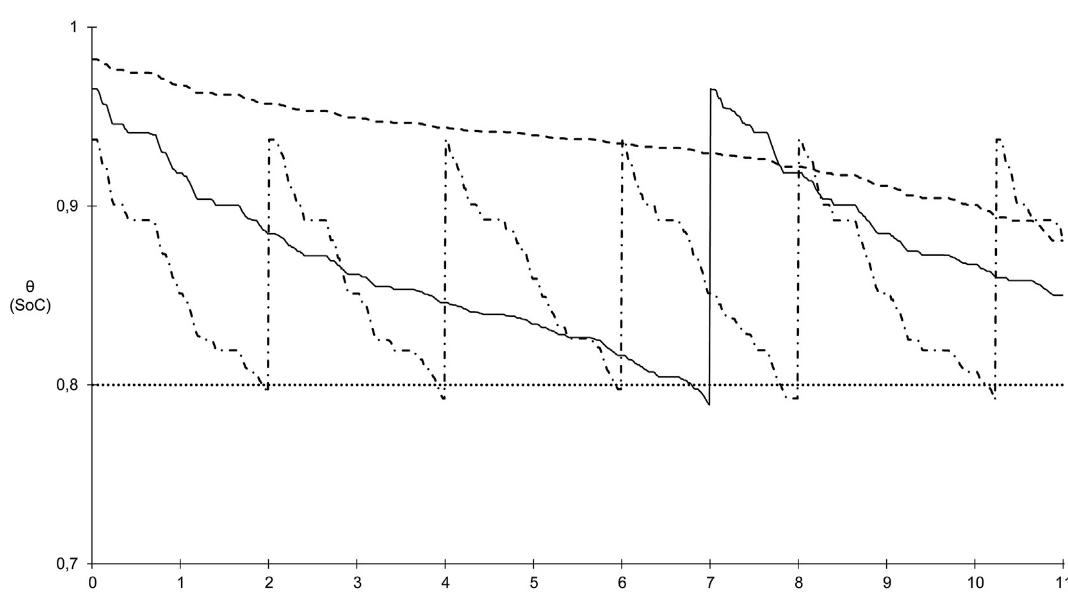

Fig. 4 – Capacity fade and replacement rate for three different charging rates, 4C (dash-dotted line), 1C (full line) and C/10 (dashed line) over 11 years. Simulation of a system of four batteries with energy content of 50 kWh, assuming even load on the batteries. End-of-life (θ_{EoL}) set at 0.8 (dotted line) and the battery packs were replaced at the end of the year where the system on average reached $\theta = 0.8$. Calendar ageing not included.

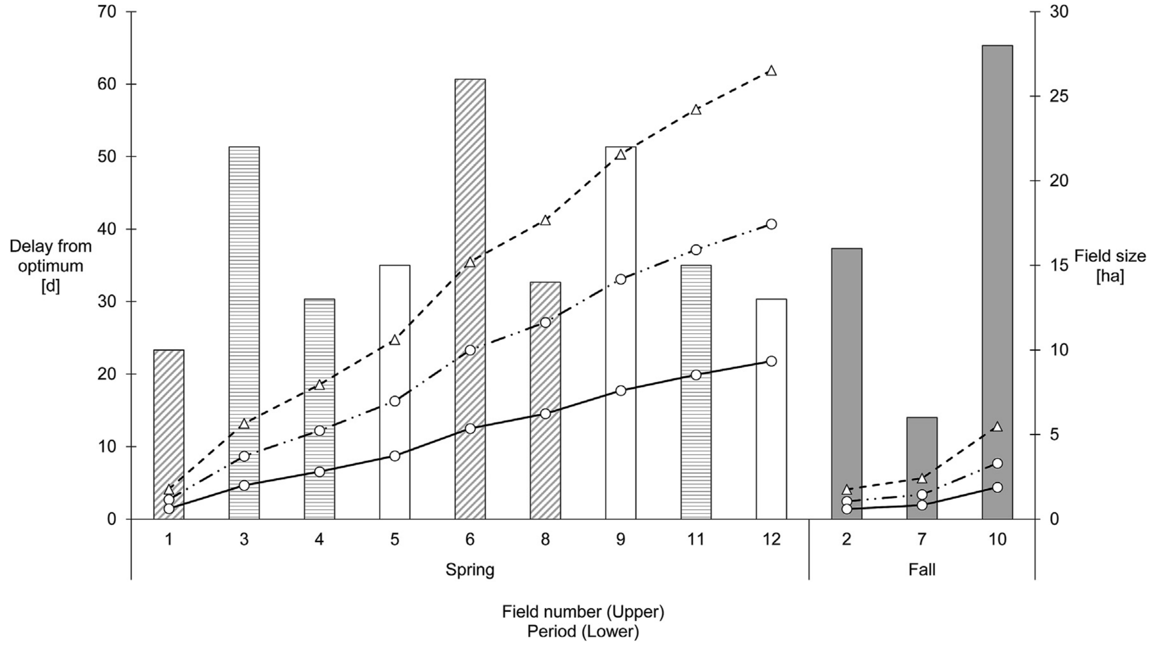

Fig. 5 – Average delay (lines, left axis) from the optimum date of sowing for scenarios with a battery electric drive (BED) tractor (dashed line) and a conventional manned diesel tractor system with two tractors (D2; full line) and one tractor (D1; dashed double-dotted line). Field sizes (bars, right axis) are shown, with the pattern and shade in columns denoting the type of grain crop grown in the field (winter wheat (grey), spring wheat (white), barley (vertical) and oats (diagonal)).

3.4.3. *Investment, operating and total annual costs*

The total cost of investment for the autonomous BED system with BES was 218,868 €, and the annual cost was 57,002 € yr^{-1}. The BED system had slightly higher investment costs and lower operating costs than the 1-vehicle diesel system (D1) and lower costs of both compared with the 2-vehicle system (D2) (Fig. 7). The investment costs for D1 were 196,554 € and the annual costs were 69,774€ yr^{-1}, while the investment

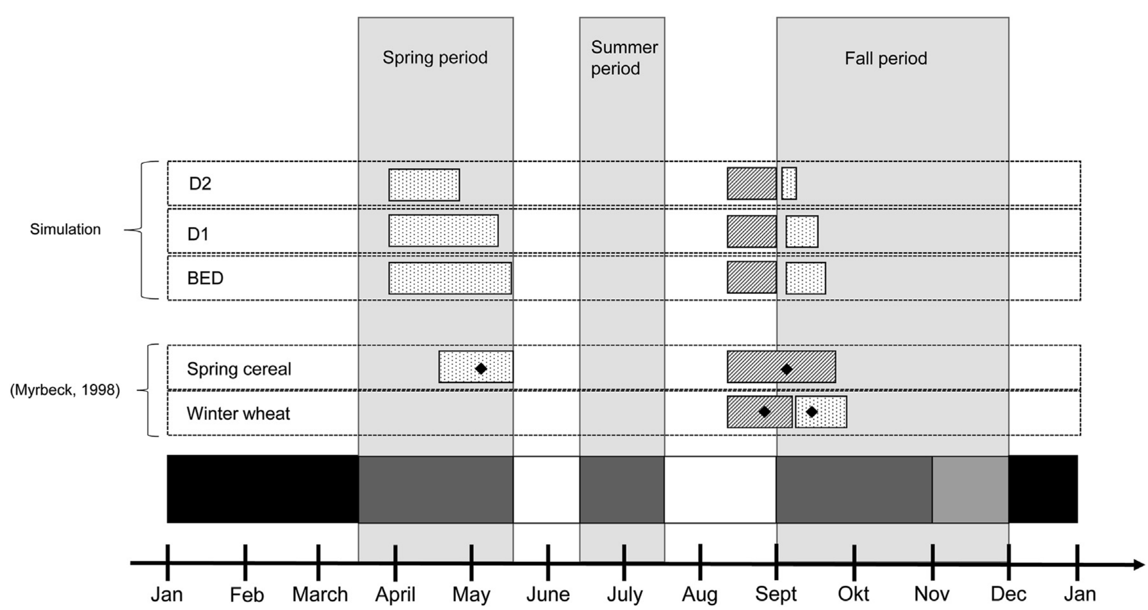

Fig. 6 – Actual sowing (dotted pattern) and harvesting (diagonal pattern) interval with mean values (black diamond) for central Sweden from Myrbeck (1998) and simulated sowing dates in scenarios with a battery electric drive (BED) tractor and a conventional manned diesel tractor system with one (D1) and two (D2) tractors. The three work periods are indicated in light grey, while non-active periods (black) and the growing period (white) are shown in the bottom bar. A one-month reserve period (medium grey) was included in the autumn period to make sure the simulation ran to completion. Ploughing was the only task performed during the reserve period.

costs for D2 were 393,108 € and the annual costs were 80,656 € yr^{-1}.

The largest fraction of the investment costs for the BED system was purchase of the tractor (41%) followed by installation of the charging system (23%) and the autonomous system (16%). For the diesel systems, the investment costs were similar for both D1 and D2, and comprised only purchase of tractor/s (97%) and cost of interest (3%).

For the diesel cases the three largest components of the annual cost (C_{AN}) were cost of investment (C_{OW}), operator cost and fuel, contributing 67–79% of the total operating costs (Fig. 8). For the BED case the three largest components were timeliness (30%), C_{OW} (23%) and operator cost (23%) for a total of 76% of $C_{AN.}$ Timeliness was a relevant component for the operating costs for all cases, at 20,847 € y^{-1} (30%) for the BED system, 13,569 € y^{-1} (19%) for D1 and 7321 € y^{-1} (9%) for D2.

3.5. *Sensitivity analysis*

A sensitivity analysis of several parameters was performed to assess their influence on different costs. The costs of batteries, autonomous system, charger installation, operator and electricity were varied in the BED case, to gain an understanding of their influence on the yearly cost of operations. In addition, the interest rate, timeliness factors, economic lifetime and the autonomous fraction of different operations and activities for the autonomous systems were varied. Absolute change, absolute sensitivity and relative sensitivity were measured.

3.5.1. *Parameter-based sensitivity analysis*

Table 7 shows the absolute sensitivity and the relative sensitivity for some key parameters included in the cost analysis. Relative sensitivity is denoted as the change in the total annual cost given a change of one unit in the given parameter.

3.5.2. *Rate of autonomy and operator factor*

The amount of autonomy is a key concept in the analysis of self-driving vehicle systems. Discussions on autonomous vehicles in agriculture usually focus on the amount of autonomy in fieldwork (Engström & Lagnelöv, 2018; Goense, 2005; Oksanen, 2015). However, for an independent generalist vehicle it is also necessary to consider additional activities, such as charging and road transport. The intricacies of on-road autonomy are a complex subject outside the scope of this article, but the scenarios of fully manned/monitored drive and fully autonomous operation were explored as a cost function, as shown in Table 8.

3.5.3. *Battery cost and lifetime*

As mentioned previously, the cost of the batteries was assumed to be low compared with other annual costs, but it is still critical for any electric vehicle. To verify the choices made and see the potential effect of other assumptions on prices and lifetimes, these parameters were varied independently.

As can be seen in Fig. 9b, the annual battery cost varied linearly with the pack cost. The battery cost was a small part of the total annual cost for all values tested and, even with the highest price in the interval, 330 € kWh^{-1} (Nykvist & Nilsson, 2015), the total annual cost was still lower than for D2 and similar to D1. The operational lifetime of the battery before replacement was important for the battery cost, as the cost decreased exponentially with increased lifetime (Fig. 9a). Extending the battery lifetime beyond the first few years is paramount to keep a low annual cost.

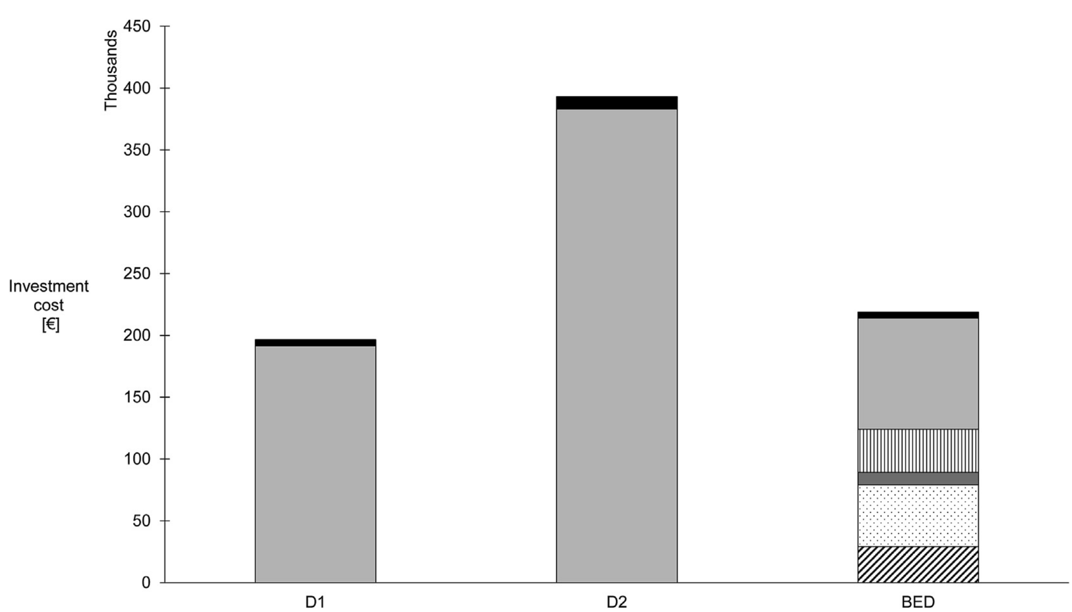

Fig. 7 – Investment costs (C_{OW}) in € for a simulated battery electric drive (BED) tractor system with autonomous capacity and two manned diesel counterparts (D1, D2). Columns show the cost of the tractor (grey), battery (diagonal stripes), charger system (dotted), battery changing system (dark grey), autonomous system (vertial stripes) and cost of interest (black).

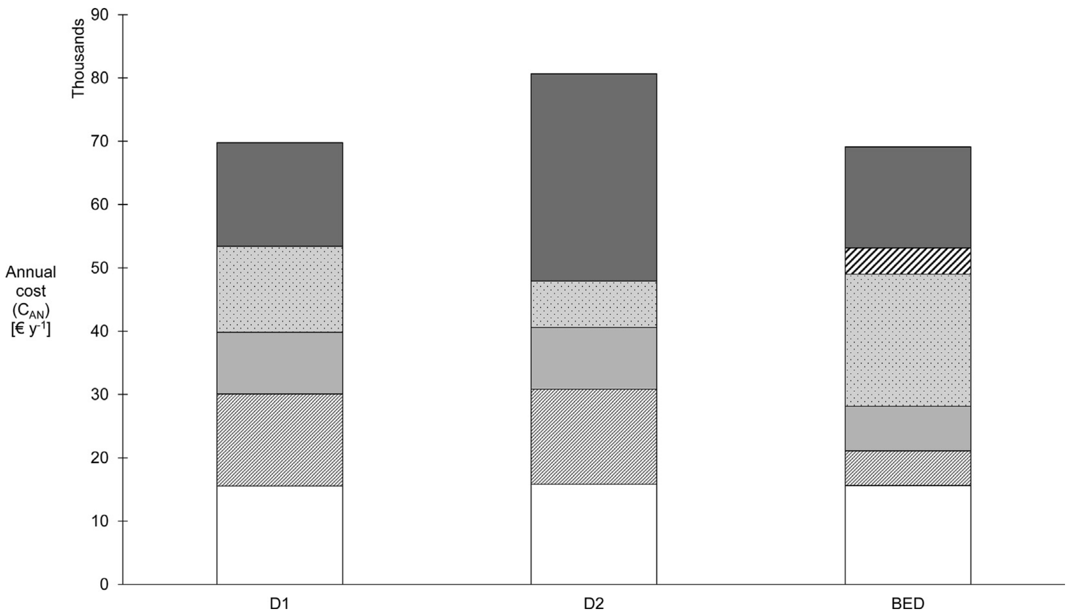

Fig. 8 – Annual cost of operation (C_{AN}) in € yr^{-1} for a simulated battery electric drive (BED) tractor system with autonomous capacity and two manned diesel counterparts (D1, D2). Columns show the annual costs of operator (white), fuel (thin diagonal stripes), maintenance (grey), timeliness (dotted on light grey background), batteries (broad diagonal stripes) and C_{OW} (annual cost of investment, dark grey).

Table 7 – Change in total annual cost given a change in a single parameter and relative sensitivity for different parameters influencing the annual cost in the battery electric drive (BED) tractor scenario. The closer the relative sensitivity is to one, the more sensitive the annual cost to changes in that parameter. Relative sensitivity of T_x is not shown as it is non-constant. In addition, changes deemed unrealistic are represented with a dash (–).

Parameter change	Absolute sensitivity, in %				Relative sensitivity
	−50%	−25%	+50%	+100%	
Investments					
Charger (c_C)	−3.3	−1.6	+3.3	+6.5	0.07
Battery (c_B)	–	−1.5	+2.9	+5.8	0.06
Tractor (c_V)	−5.6	−2.8	+5.6	+11.1	0.11
Autonomous system (c_A)	−2.2	−1.1	+2.2	+4.3	0.04
Operating costs	−50%	+50%	+100%	+200%	
Operator (c_O)	−11.3	+11.3	+22.6	+45.2	0.23
Electricity (c_E)	−4.0	+4.0	+7.9	+15.9	0.08
Timeliness factor (l)	−15.1	+15.1	+30.2	+60.3	0.30
Other	−50%	+50%	+100%	+200%	
Interest rate (i_r)	−1.9	+1.9	+3.8	+7.6	0.04
Economic life (T_x)	+16.4	−5.5	−8.2	–	–

Table 8 – Change in annual cost (C_{AN}, in %) compared with the battery electric drive (BED) case. The operator factor for three different activities (road transport, charging and fieldwork) was varied from 0 (fully autonomous operation) to 1 (fully monitored operation). In the BED case, $O_r = 0.3$, $O_c = 0.1$, $O_f = 0.1$ (section 2.3.9) and $C_{AN} = 57{,}002$ € yr^{-1} (section 3.4.3).

Operator factor	0	0.5	1
Road transport (O_r)	−13%	+9%	+30%
Charging (O_c)	−2%	+7%	+15%
Fieldwork (O_f)	−8%	+12%	+32%
All ($O_r = O_c = O_f$)	−23%	+27%	+77%

3.6. *Case-based cost analysis*

Several other cases were simulated and their cost and active time requirement calculated. The different cases included the two different battery recharging methods described in Lagnelöv et al. (2020) and vehicles with larger batteries, multiple smaller batteries, high-powered chargers, lowered working time and autonomous diesel systems (Table 9).

Figure 10 shows the different annual costs for the different cases in Table 9. Notably, all but one of the electric cases had a cost comparable or lower than the manned diesel cases,

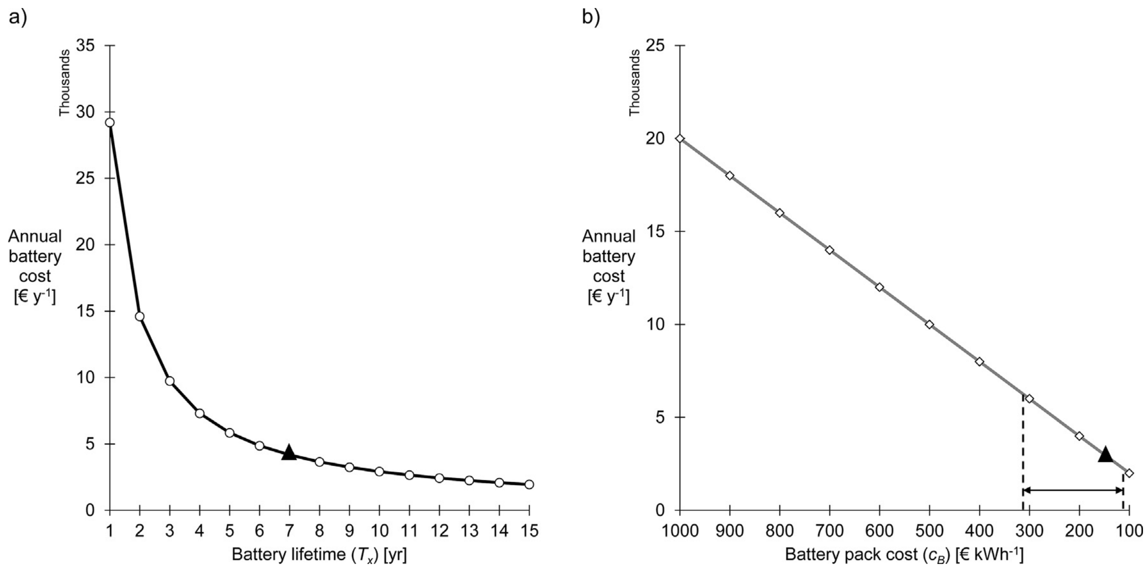

Fig. 9 – Impact on annual battery cost of a) battery lifetime before replacement and b) battery pack cost for the battery electric drive (BED) tractor case. The cost interval (dashed lines, arrow) from relevant literature is given (Comello & Reichelstein, 2019; McKerracher et al., 2020; Nykvist & Nilsson, 2015; Tsiropoulos et al., 2018). The values used in the BED case are shown as black triangles.

indicating that multiple system designs, charging systems and component sizes are competitive, even in the cases where the number of active days were higher.

In total, the autonomous diesel system (D2A) had the lowest annual cost and active number of days, indicating the high profitability of autonomy. A system with multiple smaller exchangeable batteries (BES2) had a significantly higher cost than the other BED systems, mostly due to a high number of active days, which led to high operator cost and timeliness cost. The system with four vehicles (NV4 BES) had the second lowest number of active days, but the third highest annual cost of the BED systems, due to its large investment cost and subsequent depreciation, as it provided expensive overcapacity.

For both conductive charging (CC) and BES, the systems with lowest total annual cost were those with large batteries (CC3 and BES3). This shows that the rate at which the battery ages is important, as the CC system with a higher powered charger, but one-third the energy content in batteries (CC2), had an annual battery cost that was more than seven times that of CC3, due to the rapid replacement of the batteries.

The BES studied had a lower number of yearly cycles per battery compared with CC, although they had similar total yearly cycles, as the yearly cycles were distributed on a higher number of batteries. This resulted in comparatively longer time to EOL for BES and gave a lower battery cost per kWh, even though the battery investment costs were higher (Fig. 10). All BED systems shown had lower yearly energy usage and cost compared with the diesel alternatives. Energy- and battery-related results for the different cases are shown in Table B1.

4. Discussion

4.1. Battery ageing

Battery ageing gave a large variation in MTTR between the different C-rates studied (Fig. 4). Increased rate of degradation with increased C-rate is discussed in the literature and linked to high cell temperatures, Li-plating on the negative electrode and electrolyte decomposition, which all lead to accelerated

Table 9 – Cases simulated in cost analysis. D = diesel, E = electricity, CC = conductive charging, BES = battery exchange system.

Case name	D1	D2	BED	D2A	CC 1	CC 2	CC 3	BES 2	BES 3	NV4 BES	BES 18 h
Fuel, Charging method	D	D	E/BES	D	E/CC	E/CC	E/CC	E/BES	E/BES	E/BES	E/BES
Number of vehicles (N_V)	1	2	2	2	2	2	2	2	2	4	2
Vehicle power (P_V, kW)	250	250	50	50	50	50	50	50	50	50	50
Battery energy eq. carried (E_B, kWh)	1315	1315	50	1315	50	100	50	25	50	50	50
Number of extra batteries (N_B)	–	–	2	–	–	–	–	6	2	3	2
Charging power (P_C, kW)	30,345	30,345	50	30,345	50	50	150	25	100	50	50
Number of chargers/fuel pumps (N_C)	1	1	1	1	1	1	1	2	2	3	1
Number of battery exchange stations (N_{BCS})	–	–	1	–	–	–	–	1	1	1	1
Daily working time (h, h d^{-1})	10	10	24	24	24	24	24	24	24	24	18

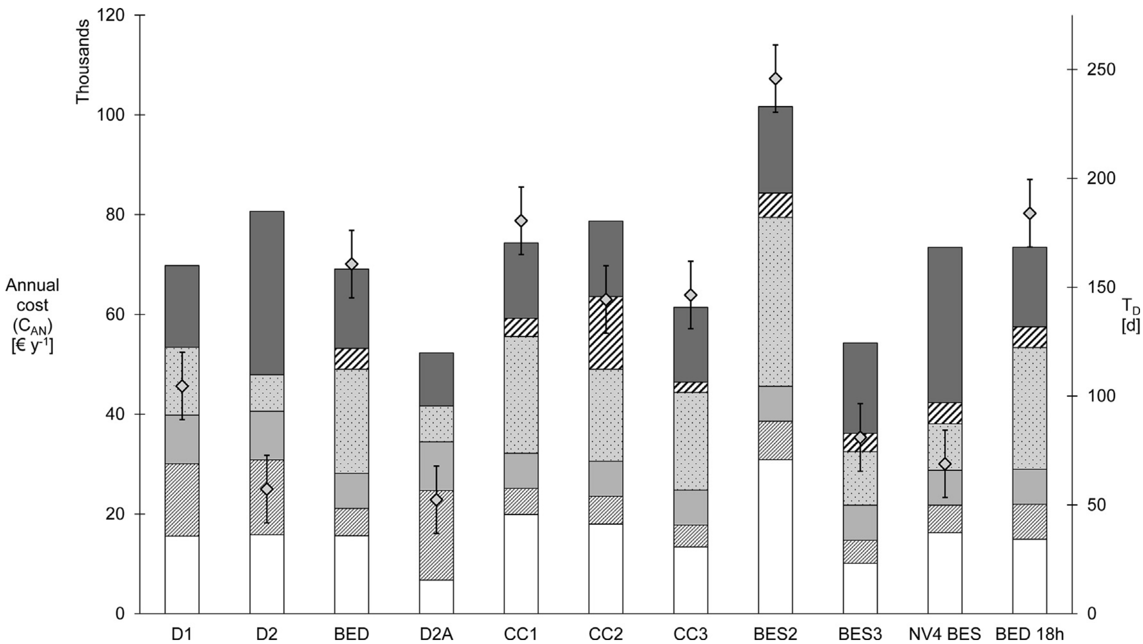

Fig. 10 — Average annual costs (bars, left axis) and active time (grey diamonds, right axis) for different cases. The annual costs are divided into costs for operator (white), fuel (thin diagonal stripes), maintenance (grey), timeliness (dotted on light grey background), battery (broad diagonal stripes) and annuity of investment (dark grey). The number of active days is shown, with error bars indicating one standard deviation.

ageing. In particular, high cell temperature is reported to be a major driver in battery ageing (Barré et al., 2013; Keyser et al., 2017; Tomaszewska et al., 2019; Uddin et al., 2016). However, Keyser et al. (2017) pointed out the difficulty in decoupling the effect of high C-rates from that of increased cell temperature in general, and the fact that different cell chemistries and designs respond differently to high C-rates. Because of this, it is difficult to compare the simulated results with literature values. However, for parameters described in this study, Keyser et al. (2017) gave a MTTR of 4–9 years for a NMC battery, depending on temperature, and de Hoog et al. (2017) showed a MCTR ranging from 1200 to 3500 cycles, which is similar to the results of this study. This indicates that the MCTR and MTTR used in this study are feasible, but further research is needed as data on the heavy duty off-road use of batteries is sparse.

By using the relationship shown in Fig. 9, the assumption of different lifetimes and the cost can be explored. As the relationship between annual cost and lifetime of the battery decreased exponentially, the most important consideration appears to be to increase the lifetime beyond the first years. In those intervals, the chosen C-rate was highly influential.

Battery size appeared to be of less importance than battery lifetime. However, the cases with larger batteries performed better than other changes in battery parameters (Fig. 10). They had a lower total annual cost and lower annual battery cost, even though their investment costs were higher. This was true for both CC and BES, with similar results. This seems to indicate that optimising the system for long-term battery use gives a better pay-off than investing in fast charging.

4.2. *Timeliness*

In previous studies (Magalhães et al., 2017; Moreda et al., 2016), it was assumed that a BED would suffer as regards capacity, due to the need for frequent recharging. This was encountered in the simulations made as the BED case had a 54% larger timeliness cost compared to D1. Inclusion of autonomy seemed to mitigate this, as BED still had a slightly lower annual cost. In addition, other cases were shown to have comparable or lower timeliness cost, indicating that with the right optimisation it is not an issue. Compared with other literature values, the resulting cost of timeliness appeared reasonable. Costs in the range 46–121 € ha^{-1} was shown for different cases with BED and 36–68 € ha^{-1} for the diesel cases. Gunnarsson and Hansson (2004) found a timeliness cost of 102 € ha^{-1} and de Toro (2005) a range of 30–145 € ha^{-1}, with an average of 60 € ha^{-1} for similar crops, conditions and climate. It is worth noting that harvest is included in both these ranges of values. However, as discussed in Lagnelöv et al. (2020), the number of workable hours in the field due to weather was lower in those studies than in other similar studies, which might explain part of the discrepancy.

The cost of timeliness is a theoretical comparison to an assumed optimal yield. As the sowing dates for BED would have been within the intervals shown by de Toro (2005); Witney (1988) and Myrbeck (1998), it is possible that the actual timeliness cost would have been lower than presented (Fig. 6). However, as it affected all cases equally, it still shows the dynamics of the concept. In addition, other climates and sites often have a wider window of suitable conditions, for example the UK (Witney, 1988), USA (ASAE, 2000; Edwards et al., 2016) and southern Europe (Savin et al., 2014). Since timeliness was not found to be an insurmountable part of the cost in the northern European climate in Sweden, it follows that this type of autonomous BED system would have a lower timeliness cost in those other regions, provided that the other parameters are similar.

4.3. Economics

For the BED case, part of the investment cost was for new infrastructure in the form of charging stations and battery changing stations, while all the infrastructure for the diesel cases was assumed to be in place, with no further need for improvement. This might appear to be an unfair comparison, but when trying to replace an existing solution it is a reality that the cost of new infrastructure must be included. Even with the installation of new infrastructure leading to a higher investment cost for BED compared with D1, the BED case had slightly lower annual costs thanks to the reduced operating costs, most notably fuel and maintenance. The annuity on investment was a relatively small part of the total annual costs, but the operating costs were of high significance (Fig. 8). For on-road vehicles, especially cars, the increased investment cost of BED vehicles is seen as a barrier to effective market penetration. For heavy duty vehicles this is a much less severe problem, as the vehicles in that market segment also have higher operating costs.

A high number of active days often involved a high cost, as it affected both timeliness (more delay) and operator costs (more hours where the vehicles must be monitored) (Fig. 10). In some exceptions, there was a trade-off with other costs, for example CC1 had a higher number of active days than CC2, but a lower cost due to the reduced battery cost. The number of active days could not be used on its own to draw conclusions on the annual cost of a system, but a high number of active days was often indicative of a system with poor optimisation, associated in turn with higher annual costs.

The actual cost of autonomous systems is difficult to determine correctly and only assumptions are possible without calculating the cost on component level, which was beyond the scope of this study. Instead, the investment cost of the autonomous system was included in the sensitivity analysis. The price of Robotti indicates that a tractor with a high level autonomy can be made for a similar price to manned tractor. Engström and Lagnelöv (2018) theorised that the removal of driver comfort systems and cabin could make for a cheaper vehicle and potentially make up for the increased cost of the autonomous system. The degree of automation is also important for the production cost of autonomous systems (Table 8). Marinoudi et al. (2019) found increased total costs at a certain level of automation for agricultural vehicles at which the component costs overtake the avoided labour cost and any further increase is economically sub-optimal. As the present study considered a highly autonomous system, it is possible that the cost of automation would have increased non-linearly and posed higher costs than presented here for highly autonomous solutions. However, unless exorbitantly expensive, it would be covered by the variations presented in the sensitivity analysis.

Fieldwork proved to be the operation for which a high degree of autonomy was most important, followed by road transport. The most time-consuming operation needed to have a high autonomy rate to have a low cost, which generally proved to be fieldwork and, for some BED cases, road transport. Road transport is a complex task to make autonomous, but there are indications that fieldwork is a more suitable task (Goense, 2005). Requiring the system to be monitored constantly ($O_{tot} = 1$) would increase the annual cost by 77%, making it more expensive than both the diesel cases studied here and generally economically unsuitable. This indicates that manned BED systems will struggle to compete in terms of costs with conventional diesel systems, whereas even partly autonomous systems may be competitive. This was somewhat explored with the BED 18 h-case, which showed a slight decrease in capacity but still had a comparable cost to the BED case with a 24-h working day, and the D1-case. It also highlights the benefit of understanding and minimising the number of hours of monitored non-productive work, most notably road transport. Due to more time spent refuelling and in transit the operator costs for BED and D1 was similar, which indicates an under capacity for the BED systems. Systems with higher battery capacity reduced the time spent in transit while having a slightly higher amount of time spent charging, which overall led to a low operator cost, notable in the CC3 and BES3 cases.

It is also worth discussing the manner in which the driver can be replaced. In this study, it was assumed that a single operator would monitor a certain fraction of the machine-hours. In reality, this function might hamper the vehicle's ability to work independently at all hours of the day, as the restrictions of human supervision would still be imposed, only at a higher level compared with a tractor driver's more direct involvement. The approach used in this study calculated the cost for every manned or monitored hour and other approaches would likely give different operator costs. Our approach was suitable for cost analysis, but there are many questions regarding general management that require further research.

4.4. Sensitivity analysis

The results from the sensitivity analysis showed that changes in the operating costs were more influential than changes in the investment costs, as the investments were distributed over the economic lifetime of the system, but changes in the operating costs were incurred directly. This indicates that in order to achieve a low annual cost, the operating costs need to be minimised and the economic lifetime maximised.

The case-based cost analysis (Fig. 10) showed the effects of different system design parameters, from large chargers to many small, replaceable batteries. The main dynamics discussed in (Lagnelöv et al., 2020) were confirmed, i.e. the difference between CC and BES was small but slightly favoured BES, $E_B < 50$ kWh led to a poorly optimised system; and a balanced ratio between battery size and charging speed is needed (here also shown as C-rate). It was also shown that cases with larger battery capacity (CC3 and BES3) had a noticeably lower annual cost compared to the diesel system, with BES3 having a comparable annual cost to D2A. This indicate that BED tractor systems can cost-effectively compete with manned and unmanned diesel systems. Additionally, the low costs obtained for most BED cases and the autonomous diesel system indicate that autonomy in an agricultural field setting can decrease the annual costs substantially.

5. Conclusions

In a simulated scenario, autonomous BED systems were found to have comparable or lower annual costs than equivalent cases with both one and two manned diesel vehicles. The BED systems had lower maintenance and fuel costs, but generally higher investment and timeliness costs and a higher number of required active days. The reduction in the operating costs outweighed the higher investment costs in the BED cases.

To ensure equal or comparable working rate to contemporary diesel systems, autonomy was shown to be necessary for the BED systems. The analysis revealed high sensitivity to degree of autonomy, with a fully monitored BED system having costs exceeding those of the diesel systems. Simulations of a diesel system running on the same assumptions as the BED systems (multiple smaller vehicles with a 24-h working day) showed low cost and high capacity, indicating the advantages of autonomy. These findings indicate that many of the predicted problems with agricultural field BEVs are solvable or can be mitigated by vehicular autonomy. In addition, this study showed that the cost of timeliness was generally larger for BED systems than for diesel systems but still resulted in a lower annual cost due to savings in operational costs.

The increased investment costs associated with BEVs proved to be a small proportion of the total annual costs of operation. Battery ageing had a significant impact on the associated costs, but using batteries larger than 50 kWh or multiple batteries extended the lifetime of the batteries significantly. In addition, it was shown that the operating costs of the vehicle systems were more influential than the investment costs. Cases that ensured low operating costs through reduced maintenance, fuel, timeliness and operator costs had lower annual costs.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This article was funded by the Swedish Government research program “STandUP for Energy” and by the Swedish Energy Agency under grant number P44831-1.

Appendix A. Battery model simulation parameters

Table A1 – Simulation and modelling parameters used in simulation of battery ageing

Parameter [unit]	Variable	Value
Ageing parameter	alpha	0.67
Surface area	Av_neg	3*0.384/rp_neg
Bruggeman coefficient for tortuosity in positive electrode	brugl_pos	2.98
Bruggeman coefficient for tortuosity in separator	brugl_sep	3.15
Initial electrolyte salt concentration [mol m^{-3}]	cl_0	1200
[mol m^{-3}]	cs_pos_max	48,000
Initial SEI layer thickness [mm]	dfilm_0	1
Maximum cell voltage [V]	E_max	4.1
Minimum cell voltage [V]	E_min	2.5
Electrolyte phase volume fraction negative electrode	epsl_neg	0.444
Electrolyte phase volume fraction positive electrode	epsl_pos	0.41
Electrolyte phase volume fraction separator	epsl_sep	0.37
Solid phase volume fraction negative electrode	epss_neg	1-epsl_neg-0.172
Solid phase volume fraction positive electrode	epss_pos	1-epsl_pos-0.170

(continued on next page)

Table A1 – (continued)

Parameter [unit]	Variable	Value
Ageing parameter [s^{-1}]	f	2.0e2
Ageing parameter	H	6.7
1C discharge current [m̂2/3600s]	i_1C	Q0*1
Constant current, charge	I_ch	i_1C
Constant current, discharge	I_dch	-i_1C
Minimum cell current for constant voltage charge	I_min_ch	i_1C/20
Ageing parameter [h]	i1C_loc	Q0/(Av_neg*L_neg)/1
Ageing parameter	J	8.40e-04
Reaction rate coefficient negative electrode [m s^{-1}]	k_neg	2e-11
Reaction rate coefficient positive electrode [m s^{-1}]	k_pos	5e-10
SEI layer conductivity [S m^{-1}]	kappa_film	5e-6
Length of negative electrode [m]	L_neg	55e-6
Length of positive electrode [m]	L_pos	40e-6
Length of separator [m]	L_sep	30e-6
Molar mass of product of side reaction [kg mol^{-1}]	M_sei	0.16
Number of cycles	no_cycles	2000*2 + 80
Initial capacity	Q0	cs_pos_max*(1–0.25)*epss_pos*L_pos*F_const
Density of product of side reaction [kg m^{-3}]	rho_sei	1.6e3
Particle radius negative electrode [m]	rp_neg	2.50e-6
Particle radius positive electrode [m]	rp_pos	0.25e-6
Cell temperature [°C]	T	20
Approximative total cycling time	t_cycling	(no_cycles+1)*10000/t_factor
Time acceleration factor	t_factor	80

Appendix B. Case-based detailed results

Table B1 – Energy and battery results from the case study. Battery lifetimes longer than the simulated 11 years are denoted 11+. The results from the BES18h case were omitted, as the case is a variant of the BED case.

Case name	C-rate	E_{tot} [kWh y^{-1}]	Energy cost [€ y^{-1}]	Eq. cycles [y^{-1}]	Eq. cycles per battery [y^{-1}]	MCTR (calculated)	MTTR [y]	Battery investment cost [€]	Battery cost per cycle [€][b]	Battery cost per kWh (over lifetime) [€]
D1	–	168,748	14,512	243[a]	–	–	–	–	–	–
D2	–	174,294	14,989	218[a]	–	–	–	–	–	–
BED	1C	91,462	7317	2464	616	4,24	6.9	29,200	6.8	0.17
D2A	–	208,994	17,973	229[a]	–	–	–	–	–	–
CC 1	1C	88,636	7091	2432	1216	4,24	3.5	14,600	3.0	0.08
CC 2	4C	93,384	7471	2554	1277	1,2	0.9	14,600	11.4	0.29
CC 3	C/10	73,069	5846	741	370	7,76	11+	43,800	5.6	0.05
BES 2	1C	116,966	9357	5834	729	4,24	5.8	29,200	6.7	0.33
BES 3	1C	79,302	6344	1,09	272	4,24	11+	58,400	13.4	0.17
NV4 BES	1C	95,766	7661	2544	363	4,24	11+	51,100	11.7	0.29
BES 18H	1C	87,616	7009	2354	588	4,24	7.2	29,200	6.2	0.16

[a]For diesel systems, the term "cycling" is best replaced with "refuellings."
[b]Calculated on the annuity cost of batteries and yearly cycles per battery.

REFERENCES

ASAE. (2000). Agricultural machinery management data. In *ASABE*. St. Joseph, MI, USA: American Society of Agricultural Engineers.

Bakken, M., Moore, R., & From, P. (2019). End-to-end learning for autonomous crop row-following. *IFAC-PapersOnLine, 52*–30, 102–107. https://doi.org/10.1016/j.ifacol.2019.12.505

Barré, A., Deguilhem, B., Grolleau, S., Gérard, M., Suard, F., & Riu, D. (2013). A review on lithium-ion battery ageing mechanisms and estimations for automotive applications. *Journal of Power Sources, 241*, 680–689. https://doi.org/10.1016/j.jpowsour.2013.05.040

Berg, H. (2015). *Batteries for electric vehicles*. Cambridge, England: Cambrigde University Press.

Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2018). Cost-based analysis of autonomous mobility services. *Transport Policy, 64*, 79–91. https://doi.org/10.1016/j.tranpol.2017.09.005

Brundrett, S. (2014). *Industry analysis of autonomous mine haul truck commercialization* (Master Thesis). University of British Columbia. Retrieved from https://core.ac.uk/download/pdf/56378551.pdf.

Caban, J., Vrabel, J., Sarkan, B., Zarajczyk, J., & Marczuk, A. (2018). Analysis of the market of electric tractors in agricultural production. *Innovative Technologies in Engineering Production, 244*, 1–10. https://doi.org/10.1051/matecconf/201824403005

Comello, S., & Reichelstein, S. (2019). The emergence of cost effective battery storage. *Nature Communications, 10*(2038). https://doi.org/10.1038/s41467-019-09988-z

COMSOL Multiphysics. (2020). 1D lithium-ion battery model for the capacity fade tutorial (Version application ID: 12667): COMSOL MultiPhysics. Retrieved from https://www.comsol.se/model/1d-lithium-ion-battery-model-for-the-capacity-fade-tutorial-12667.

Daziano, R. A., Sarrias, M., & Leard, B. (2017). Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. *Transportation Research Part C: Emerging Technologies, 78*, 150–164. https://doi.org/10.1016/j.trc.2017.03.003

Delucchi, M. A., & Lipman, T. E. (2010). Lifetime cost of battery, fuel-cell and plug-in hybrid electric vehicles. In G. Pistoia (Ed.), *Electric and hybrid vehicles - Power sources, models, sustainability, infrastructure and the market* (1st ed. ed.). Elsivier. https://doi.org/10.1016/B978-0-444-53565-8.00002-6.

Edwards, G., Dybro, N., Munkholm, L., & Sörensen, C. (2016). Assessing the actions of the farm managers to execute field operations at opportune times. *Biosystems Engineering, 144*, 38–51. https://doi.org/10.1016/j.biosystemseng.2016.01.011

Ekström, H., & Lindberg, G. (2015). A model for predicting capacity fade due to SEI formation in a commercial Graphite/LiFePO4 cell. *Journal of the Electrochemical Society, 162*, A1003–A1007. https://doi.org/10.1149/2.0641506jes

Engström, J., & Lagnelöv, O. (2018). An autonomous electric powered tractor - simulations of all operations on a Swedish dairy farm. *Journal of Agricultural Science and Technology, 8*(3), 182–187. https://doi.org/10.17265/2161-6256/2018.03.006

Fagnant, D. J., Kockelman, K. M., & Bansal, P. (2015). Operations of shared autonomous vehicle fleet for Austin, Texas, market. *Transportation Research Record: Journal of the Transportation Research Board*, (2536), 98–106. https://doi.org/10.3141/2536-12

Goense, D. (2005). The economics of autonomous vehicles in agriculture. In *Paper presented at the 2005 ASAE annual international meeting, Tampa, Florida*. https://doi.org/10.13031/2013.18842

Gunnarsson, C. (2008). *Timeliness costs in grain and forage production systems* (Doctoral dissertation). Uppsala, Sweden: Swedish University of Agricultural Sciences. Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:slu:epsilon-2679 (2008:102).

Gunnarsson, C., & Hansson, P.-A. (2004). Optimisation of field machinery for an arable farm converting to organic farming. *Agricultural Systems, 80*(1), 85–103. https://doi.org/10.1016/j.agsy.2003.06.005

Gunnarsson, C., Spörndly, R., Rosenqvist, H., De Toro, A., & Hansson, P.-A. (2009). A method of estimating timeliness costs in forage harvesting illustrated using harvesting systems in Sweden. *Grass and Forage Science, 64*(3), 276–291. https://doi.org/10.1111/j.1365-2494.2009.00693.x

de Hoog, J., Timmermans, J.-M., Ioan-Stroe, D., Swierczynski, M., Jaguemont, J., Goutam, S., … Van Den Bossche, P. (2017). Combined cycling and calendar capacity fade modeling of a Nickel-Manganese-Cobalt Oxide Cell with real-life profile validation. *Applied Energy, 200*, 47–61. https://doi.org/10.1016/j.apenergy.2017.05.018

Keyser, M., Pesaran, A., Li, Q., Santhanagopalan, S., Smith, K., Wood, E., … Markel, A. (2017). Enabling fast charging – battery thermal considerations. *Journal of Power Sources, 367*, 228–236. https://doi.org/10.1016/j.jpowsour.2017.07.009

Lagnelöv, O., Larsson, G., Nilsson, D., Larsolle, A., & Hansson, P.-A. (2020). Performance comparison of charging systems for autonomous electric field tractors using dynamic simulation. *Biosystems Engineering, 194*, 121–137. https://doi.org/10.1016/j.biosystemseng.2020.03.017

Lampridi, M. G., Kateris, D., Vasileiadis, G., Marinoudi, V., Pearson, S., Sørensen, C. G., … Bochtis, D. (2019). A case-based economic assessment of robotics employment in precision arable farming. *Agronomy, 9*(175). https://doi.org/10.3390/agronomy9040175

Le, T. D., Ponnambalam, V. R., Gjevestad, J. G. O., & From, P. J. (2020). A low-cost and efficient autonomous row-following robot forfood production in polytunnels. *Journal of Field Robotics, 37*, 309–321. https://doi.org/10.1002/rob.21878

Lindgren, M., Pettersson, O., Hansson, P.-A., & Norén, O. (2002). Jordbruks- och anläggningsmaskiners motorbelastning och avgasemissioner [Engine load pattern and engine exhaust gas emissions from off-road vehicles]. Retrieved from http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A959556.

Magalhães, R. O., Vieira da Assunção, M., Santos, J. P. M., da Silva, E. V., de Gonzaga Ferreira, L., Magalhães, R. R., & Ferreira, D. D. (2017). Review on applications of electric vehicles in the countryside. *Rural Engineering, 47*. https://doi.org/10.1590/0103-8478cr20161076

Marinoudi, V., Sørensen, C. G., Pearson, S., & Bochtis, D. (2019). Robotics and labour in agriculture. A context consideration. *Biosystems Engineering, 184*, 111–121. https://doi.org/10.1016/j.biosystemseng.2019.06.013

Maskinkalkylgruppen. (2020). Maskinkostnader 2020 [machine costs 2020]. Retrieved from Maskinkalkylgruppen: http://maskinkostnader.se/.

McKerracher, C., Izadi-Najafabadi, A., ODonovan, A., Albanese, N., Soulopolous, N., Doherty, D., … Grant, A. (2020). *BNEF electric vehicle outlook 2020*. BloombergNEF. Retrieved from https://about.bnef.com/electric-vehicle-outlook/.

Mocera, F., & Soma, A. (2020). Analysis of a parallel hybrid electric tractor for agricultural applications. *Energies, 13*(12), 3055. https://doi.org/10.3390/en13123055

Moreda, G. P., Muñoz-García, M. A., & Barreiro, P. (2016). High voltage electrification of tractor and agricultural machinery – a review. *Energy Conversion and Management, 115*, 117–131. https://doi.org/10.1016/j.enconman.2016.02.018

Myrbeck, Å. (1998). *Swedish Agricultural and Horticultural crops (PM1/98)*. Solna, Sweden: Retrieved from Swedish Chemicals Agency. https://www.kemi.se/publikationer/pm/1998/pm-1-98-swedish-agricultural-and-horticultural-crops.

Nilsson, B. (1976). In *Planering av jordbrukets maskinsystem. Problem, modeller och tillämpningar. [The planning of farm machinery systems - Problems, models and applications]*. Uppsala, Sweden: Swedish University of Agricultural Sciences (Vol. Report no. 38).

Nykvist, B., & Nilsson, M. (2015). Rapidly falling costs of battery packs for electric vehicles. *Nature Climate Change, 5*, 329–332. https://doi.org/10.1038/nclimate2564

Oksanen, T. (2015). Accuracy and performance experiences of four wheel steered autonomous agricultural tractor in sowing operation. In L. Mejias, P. Corke, & J. Roberts (Eds.), *Field and service robotics* (Vol. 105, pp. 425–438). Berlin: Springer-Verlag Berlin. https://doi.org/10.1007/978-3-319-07488-7_29.

Olt, J., Traat, U., & Kuut, A. (2010). Maintenance costs of intesively used self-propelled machines in agricultural companies. In *Paper presented at the 9th international scientific conference on engineering for rural development, Jelgava, Latvia*.

Pettersson, O., & Davidsson, C. (2009). *Kostnader för maskinunderhåll vid spannmålsproduktion [maintenance costs for machinery in grain production]*. Uppsala, Sweden: Retrieved from

JTI - Institutet för Jordbruks- och miljöteknik. http://urn.kb.se/resolve?urn=urn%3Anbn%3Ase%3Ari%3Adiva-1905.

Propfe, B., Redelbach, M., Santini, D. J., & Friedrich, H. (2012). Cost analysis of plug-in hybrid electric vehicles including maintenance & repair costs and resale values. *World Electric Vehicle Journal, 5*, 886–895. https://doi.org/10.3390/wevj5040886

Reif, K., & Dietsche, K.-H. (2014). Bosch automotive handbook. In K. Reif (Ed.), *Robert bosch GmbH*. Germany: John Wiley & Sons Ltd.

Reiser, D., Sehsah, E., Bumann, O., Morhard, J., & Griepentrog, H. W. (2019). Development of an autonomous electric robot implement for intra-row weeding in Vineyards. *Agriculture-Basel, 9*(1), 12. https://doi.org/10.3390/agriculture9010018

Rotz, C. A., & Harrigan, T. M. (2005). Predicting suitable days for field machinery operations in a whole farm simulation. *Applied Engineering in Agriculture, 24*(4), 563–571. https://doi.org/10.13031/2013.18563

SAE. (2018). In *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles* (Vol. J3016_201806). Society of Automotive Engineers (SAE). https://www.sae.org/standards/content/j3016_201806/.

Savin, L., Matic-Kekic, S., Dedovic, N., Simikic, M., & Tomic, M. (2014). Profit maximisation algorithm including the loss of yield due to un certain weather events during harvest. *Biosystems Engineering, 123*, 56–67. https://doi.org/10.1016/j.biosystemseng.2014.05.002

Solus Group. (2019). Automatic transfer carriages. In *Battery handling equipment. St. Louis, MO, USA*. https://solusgrp.com/pdf/PL-1500%20Automatic%20Transfer%20Carriage.pdf.

SPBI. (2020). Diesel - prices and taxes. Retrieved from https://spbi.se/statistik/priser/diesel/.

Stamps, A. T., Holland, C. E., White, R. E., & Gatzke, E. P. (2005). Analysis of capacity fade in a lithium battery. *Journal of Power Sources, 150*, 229–239. https://doi.org/10.1016/j.jpowsour.2005.02.033

Statistics Sweden. (2019). *Jordbruksstatistisk sammanställning 2019* [Agricultural statistics 2019]. Statistics Sweden https://jordbruksverket.se/download/18.5b7c91b9172c01731757d898/1592479793521/2019.pdf.

Statistics Sweden. (2020). Prices on electricity for industrial consumers. Retrieved from https://www.scb.se/en/finding-statistics/statistics-by-subject-area/energy/price-trends-in-the-energy-sector/energy-prices-on-natural-gas-and-electricity/pong/tables-and-graphs/average-prices-by-half-year-2007/prices-on-electricity-for-industrial-consumers-2007/.

Swedish Energy Agency. (2019). Installera en laddstation till ditt företag. [Installing a charging station for you company]. Retrieved from http://www.energimyndigheten.se/klimat–miljo/transporter/energieffektiva-och-fossilfria-fordon-och-transporter/laddinfrastruktur/installera-en-laddstation/installera-en-laddstation-till-ditt-foretag/.

The Government of Sweden. (2013). *Fossilfrihet på väg. (SOU 2013:84). The goverment offices of Sweden*. Stockholm, Sweden: Ministry of the Environment.

Thomas, K. E., Newman, J., & Darling, R. M. (2002). Mathematical modeling of lithium batteries. In *Advances in Lithium-ion batteries*. Retrieved from https://escholarship.org/uc/item/6905515d.

Tomaszewska, A., Chu, Z., Feng, X., O'Kane, S., Liu, X., Chen, J., … Wu, B. (2019). Lithium-ion battery fast charging: A review. *eTransportation, 1*. https://doi.org/10.1016/j.etran.2019.100011

de Toro, A. (2005). Influences on timeliness costs and their variability on arable farms. *Biosystems Engineering, 92*(1), 1–13. https://doi.org/10.1016/j.biosystemseng.2005.06.007

Tsiropoulos, I., Tarvydas, D., & Lebedeva, N. (2018). *Li-ion batteries for mobility and stationary storage applications - Scenarios for costs and market growth (JRC113360)*. Luxembourg: Retrieved from Publications Office of the European Union. https://doi.org/10.2760/87175

Uddin, K., Perera, S., Widanage, D., & Somerville, L. (2016). Characterising lithium-ion battery degradation through the identification and tracking of electrochemical battery model parameters. *Batteries, 2*(13). https://doi.org/10.3390/batteries2020013

Vedder, B., Vinter, J., & Jonsson, M. (2018). A low-cost model vehicle testbed with accurate positioning for autonomous driving. *Journal of Robotics*, 1–11. https://doi.org/10.1155/2018/4907536, 2018.

Wenzl, H., Baring-Gould, I., Kaiser, R., Liaw, B. Y., Lundsager, P., Manwell, J., … Svoboda, V. (2005). Life prediction of batteries for selecting the technically most suitable and cost effective battery. *Journal of Power Sources, 144*, 373–384. https://doi.org/10.1016/j.jpowsour.2004.11.045

Witney, B. (1988). *Choosing and using farm machines*. London, England: Longman Scientific & Technical.

Wu, G., Inderbitzin, A., & Bening, C. (2015). Total cost of ownership of electric vehicles compared to conventional vehicles:A probabilistic analys is and projection across market segments. *Energy Policy, 80*, 196–214. https://doi.org/10.1016/j.enpol.2015.02.004. Retrieved from.

Young, S. N., Kayacan, E., & Peschel, J. M. (2018). Design and field evaluation of a ground robot for high-throughput phenotyping of energy sorghum. *Precision Agriculture*, 1–26. https://doi.org/10.1007/s11119-018-9601-6