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Assessment of power characteristics of unmanned tractor for operations on peat fields

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Abstract. In this article, power characteristics of a state-of-the-art unmanned ground vehicle (UGV) are characterised. It is demonstrated that in terms of power characteristics requirements, purpose-built computer aided autonomous UGV systems are capable of replacing systems that utilise conventional tractors in peat field operations, with milled peat extraction operations as a case study. The authors demonstrate the viability of the UGV in achieving optimal mobility capabilities in operating on peatland surface. The UGV of interest was assessed for two operations of milled peat extraction: milling and harrowing. For both operations, the power consumption of the UGV and the drawbar pull of the implements (passive miller and harrower) were measured and analysed. The required drawbar pull values of the investigated implements remained in the range of 4–8 kN, which corresponded to the drawbar power of 14–36 kW. It was found that the UGV of interest is capable of carrying out milled peat operations in terms of traction capacity. However, it was found that the power supply capacity to be insufficient, thus requiring an improved solution.

Key words: agriculture, automation, drawbar pull, drawbar power, robotic and autonomous systems, UGV.

INTRODUCTION

The introduction and vigorous implementation of Robotic and Autonomous Systems (RAS) has been going on for several decades (Lewis & Ge, 2006; Duckett et al., 2018; Roldán et al., 2018; Bonadies & Gadsden, 2019; Moysiadis et al., 2021), but so far the successful utilisation of such systems has been limited. The main constraints described as unreliable guidance systems, communications delays (Aravind et al., 2017), lack of supporting infrastructure (Hajjaj & Sahari, 2016). As well, it is noted that the overall cost of robotic systems performing agricultural tasks have not yet reached a critical cost value that supports a widespread use of these systems (Bechar & Vigneault, 2016; Bechar & Vigneault, 2017).

To conduct computer aided agricultural tasks, the first option is to equip current tractors with sensors (Reina et al., 2016) and remote-control technology (Adams, 2019), but as the RAS technology matures, it has become clear that different tasks can be performed more efficiently with the supporting autonomous capabilities (Kurita et al., 2017). Although tractors have undergone over a century of development and their design makes them universally adaptable to most tasks in agriculture, their efficiency is optimal only for certain operations (Bochtis et al., 2019).

Current autonomous functions software solutions mainly focus on fleet monitoring, particularly concerning the vehicles' position and status; however, in most cases they are not designed to automate production. Whereas UGV solutions in both military and civilian markets are focused on systems in which a single operator controls only one machine (BAE Systems, 2021; ECA Group, 2021), the capability of controlling a fleet of multiple UGV-s is not available on the market. By now, the level of autonomy is approaching the state of development that will allow the introduction of commercial off-the-shelf unmanned systems soon.

Peat fields are mostly remote areas closed to the public (Alakangas et al., 2012), therefore a safer and suitable candidate for piloting robotic systems with autonomous functions. In 2009, a robotic system with three customised autonomous tractors successfully performed peat extraction tasks (Johnson et al., 2009). This experiment, although over a decade old, demonstrated that automated milled peat extraction can be feasible.

Prerequisites for these developments are that the autonomous functions are designed in a way that supports the automation, making them the enabler of the robotic system, such as:

1. Teleoperation (Small et al., 2018).
2. Obstacle Detection and Avoidance (Zhou et al., 2012; Tabor et al., 2015).
3. Waypoint Navigation (Bayar et al., 2016; Silverberg & Xu, 2019; Madridano et al., 2021).
4. Formation Control (Kamel et al., 2020).
5. Swarming (Bayındır, 2016; Tan et al., 2016).

Depending on various factors (quality of the peat, production area size, etc.), the production of milled peat can be carried out differently (Alakangas et al., 2012):

1. re-ridging (Peco) method;
2. conveyer belt (Haku) method;
3. mechanical harvesting method;
4. vacuum harvesting method.

For all these methods, the first step is milling. In the case of milling, a thin layer of peat is removed from the deposit and left to dry. Milling usually takes place during the day, when the moisture content of the air is optimal for drying the peat. When the removed layer of peat is dry enough, the next step is to turn the peat with the operation called harrowing. Harrowing is meant to speed up the drying process even further. Depending on the weather conditions (rain, humidity, amount of solar radiation, wind), the number of turns can be 1–5. If it is no longer necessary to perform the harrowing, the peat is collected according to the method. For example, the Haku method uses a ridger, a conveyer belt collector, and trailers. The choice of method depends on various factors, such as the quality of the peat (dark peat, white peat), the surface area to be extracted, etc.

Although the different stages of operation have different energy requirements, it has become a tradition for all of these stages of operation to use general-purpose tractors with high power output and high-fuel-consumption internal combustion engines. The reason for this is that such tractors, with their versatility, are able to do carry out a variety of operations, depending on the energy needs. This versatility makes the use of tractors flexible, while for lower energy operations, large tractors are clearly oversized (Casals et al., 2016; He et al., 2019).

The underlying hypothesis of this research is that optimally designed automated UGVs can replace conventional tractors in milled peat extraction operations in terms of drawbar pull and energy consumption. To do this, the power and energy characteristics of one representative robotic system of interest are assessed by experimental setup. The robotic system of interest was chosen by the fact that it met the requirements of peatland terrain tractability and drawbar pull of the milled peat extraction implements. The novelty of the concept of utilising automated UGVs for milled peat extraction is that the fleet of conventional tractors can be replaced with a centrally controlled fleet of low-fuel-consumption robotic agents. It has been shown previously (Kägo et al., 2021) that this kind of development has the potential to reduce the demand for labour, thus lowering overall operational costs and environmental impacts.

MATERIALS AND METHODS

For the field experiments, the Multiscope by the Estonian UGV-manufacturer Milrem Robotics is used (Fig. 1) (Milrem, 2021). The platform consists of two track modules which are mechanically and electrically connected to each other. Due to the tracks, the UGV has suitable properties for moving in peatlands. The diesel-hybrid powertrain consists of a) a generator, b) a battery pack and c) two electric motors, one for each track module. As the generator constantly charges the battery pack, the batteries give out power for the electric motors which in turn generate the track propulsion. The main characteristics of the UGV are depicted in Table 1.

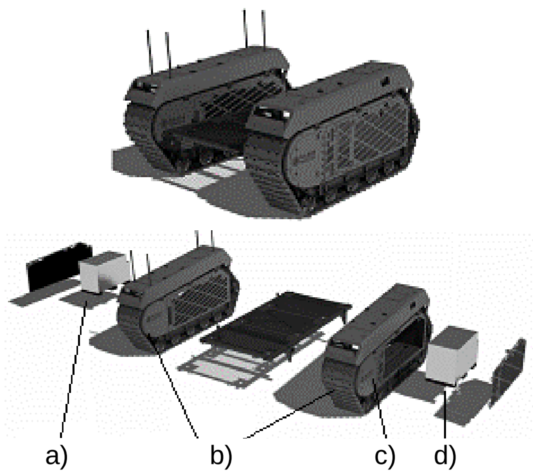

Figure 1. Structure diagram of the robotic system of interest used in the field measurement showing the position of the a) battery pack, b) track modules, c) fuel tank and d) the diesel generator.

The control techniques applied to the UGV of interest are categorised as following (Fig. 2):

1. Remote control (Stevenson et al., 2019)
   a. Line-of-Sight remote control (LOS);
   b. Beyond-Line-of-Sight remote control (BLOS).
2. Wired control.
3. Control by AI.

'Remote Control' means that the UGV is controlled by the operator using an interface (one- handed, two-handed, control station).

The operator gives commands to the UGV through the interface based on direct visual observation or by using sensor information (for example, camera feed) from the

UGV sensors. The control unit can have a direct Line-of-Sight (LOS) contact with the UGV or, if the UGV is out of visual range, have a Beyond-Line-of-Sight (BLOS) contact. In the last case, the control of the UGV is conducted only based on sensor information.

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5. Wired control.
6. Control by AI.

Table 1. The main characteristics of the UGV under evaluation

Name	Value
Dimensions (L×W×H)	240×200×115 cm
Maximum slope	60%
Maximum side slope	30%
Ground clearance	40–60 cm
Maximum speed	20 km h^{-1}
Net weight	1,630 kg
Payload capacity	1,200 kg
Specific ground-pressure	16.7 kPa
Maximum traction force	21 kN
Line of sight (LOS) control range	1,500 m
Engine power	(2×19 kW) 38 kW
Control	Remote Control (LOS, BLOS), wired, ‘Waypoint Navigation’, ‘Follow Me’

‘Remote Control’ means that the UGV is controlled by the operator using an interface (one-handed, two-handed, control station). The operator gives commands to the UGV through the interface based on direct visual observation or by using sensor information (for example, camera feed) from the UGV sensors. The control unit can have a direct Line-of-Sight (LOS) contact with the UGV or, if the UGV is out of visual range, have a Beyond-Line-of-Sight (BLOS) contact. In the last case, the control of the UGV is conducted only based on sensor information.

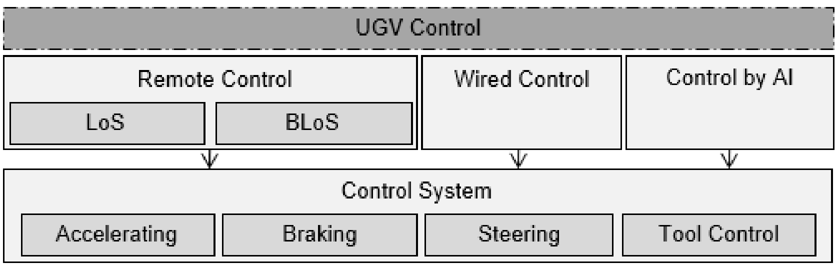

Figure 2. The control of the UGV is divided into three subcategories: a) remote control, b) wired control, c) control by AI. The control system is responsible for the d) acceleration, e) braking, f) steering, and g) tool control.

‘Wired Control’ is used mostly for cases, where the UGV is relatively near to the operator, for example, in operating in a maintenance area.

In cases, where the safety concerns are relatively low (for example, operating the UGV in a mostly empty peat field), the control of the UGV can be handed over to the autonomous functions (to the AI – *Artificial Intelligence*).

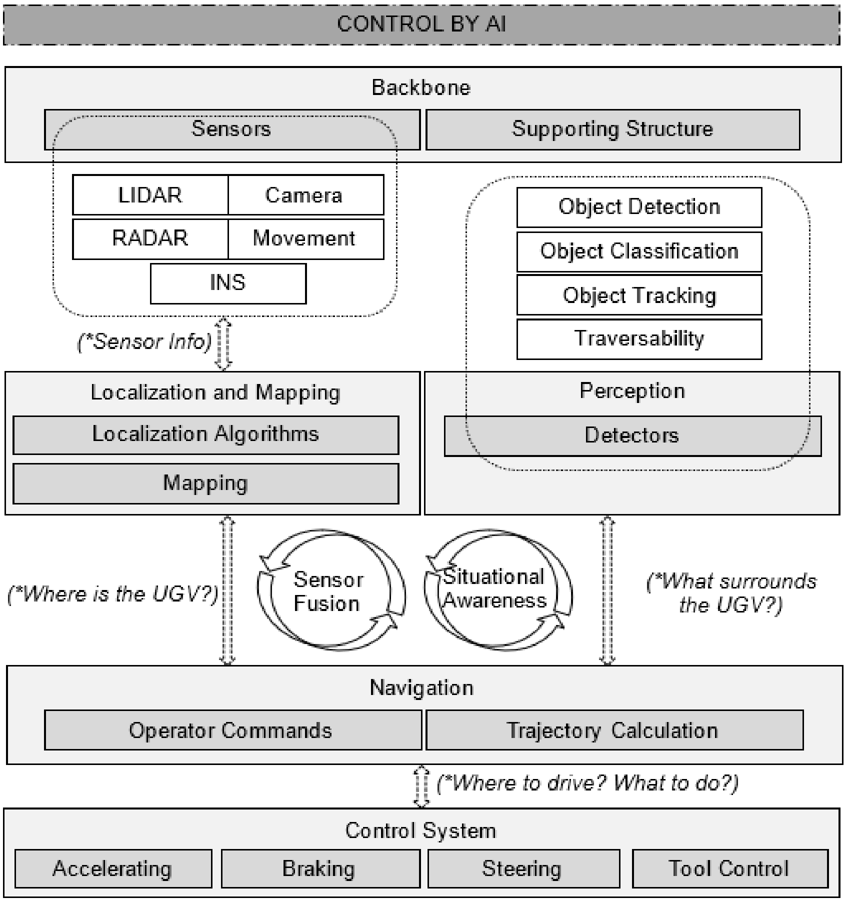

Figure 3. The 'Control by the AI' consists of five major cornerstones: a) localization and mapping, b) perception, c) navigation, d) backbone and support structure, and e) control system.

The 'Control by AI' is based on the following (Fig. 3). First, is has to be determined, where the vehicle is located. For that, localization and mapping techniques are used, which both rely on sensor information. Different types of sensors are used:

1. LIDARs (Li & Ibanez-Guzman, 2020).
2. Cameras (Chapel & Bouwmans, 2020).
3. RADARs (Javadi & Farina, 2020).
4. Vehicle movement sensors.
5. INS (Inertial Navigation System), which consist of (Konrad et al., 2018)
   a. GNSS sensor;
   b. Inertial Measurement Unit (IMU).

After the position of the vehicle is determined, it is necessary to know what it is surrounded by. For that, different types of perception techniques are used, for example:

1. Object Detection: find objects based by the output of the sensors.
2. Object Tracking (Luo et al., 2021): provide information about the location of objects over time (for example, a person in front of the UGV used in 'Follow Me' mode (Islam et al., 2019)).

3. Object Classification (Kim et al., 2021.): tell the outputs of the sensor what it is. For example, in camera view, is the object a road, car, person, etc.

4. Traversablity (Aggarwal & Kumar, 2020): provide information about the surroundings around the UGV, where it can and cannot drive, and how well it is possible. Includes sensor fusion (Sock et al., 2016).

When the positioning and the surroundings are confirmed, then, based on operator input, the 'UGV Navigation Control' conducts trajectory calculations to be used by the UGV.

Based on the calculated trajectory, the 'Control System' starts moving the UGV. Basically, the vehicle control system conducts three high-level tasks: 1) accelerating, 2) braking, 3) steering. Additional tasks during the drive, such as moving the tools, are also performed by the 'Control System'.

All localization, mapping, and perception is based on an autonomous navigation backbone with support structures and various sensors (LIDARs, camera, vehicle motion sensors, RADARs, Inertial Navigation System (INS) consisting of GNSS and Inertial Measurement Unit (IMU)) (Zhu et al., 2019).

For this experiment, the UGV was controlled by the 'LOS remote control'. Although other control methods can be used, this method was chosen because this experiment (assessment of power characteristics of the UGV) does not require a high level of autonomy. The goal of the experiment was to provide evidence that the UGV of interest is capable of performing operations peat fields.

The UGV was assessed for two operations of milled peat extraction: milling and harrowing. For both operations, the power consumption of the UGV and the drawbar pull of the implements, passive miller and harrower (Fig. 4), were measured (Adamchuk et al., 2016; Bulgakov et al., 2020). The towed implements were used as if it were used by a conventional tractor–no changes were made in their dimensions or other parameters.

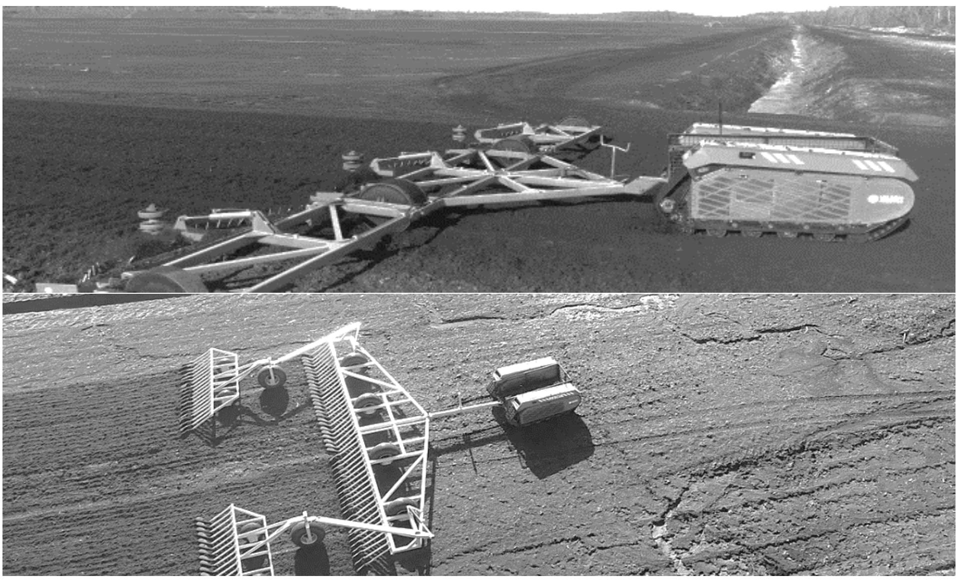

Figure 4. (up) The passive miller and (down) the harrower used in the experiment. For both implements the drawbar pull and drawbar power were determined.

The field measurements were carried out on the peat fields of Kraver AS in Viljandi County, Estonia (coordinates 58.542467, 25.860802) with ambient temperature of 10–12 °C, wind speed 2–3 m s^{-1}, no rain, relative air humidity 80%.

The data obtained from field measurements allowed the evaluation of the capability of the UGV to operate in peatland operations.

The experimental setup consists of two parts:

1. The measurement of the drawbar pull of two peat extraction implements: a) harrower, b) passive miller. The two peat extraction implement are described in Table 2.

2. The measurement of generated power by the UGV.

To measure the drawbar pull, a force transducer is connected in series between the towed implement (a passive miller and a harrower) and the drive mechanism. In this case, KAF 100 kN force transducer by A.S.T Gruppe was used (KAF-S Force Transducer, 2021). The implement is towed for at least 10 s so that the drawbar pull values can be recorded. The data is recorded with a time interval of 0.01 s. The previous procedure is repeated at varied speeds.

Table 2. The main characteristics of the towed peat extraction implements

Name	Value
Model	JLK-19S (Peatmax, 2021)
Producer	Peatmax (Finland)
Working width	12–18 m
Working depth	20 mm
Weight	1,800 kg
Name	Value
Model	84306900 (Elva EPT, 2021)
Producer	Elva EPT (Estonia)
Working width	9.5 m
Working depth	20 mm
Weight	900 kg

The values were chosen that they would correspond to the typical towing speeds for peat extraction equipment. By measuring simultaneously the drawbar pull F and operational speed v, the power consumption P_i of the implements can be determined. As the UGV was assigned to carry out milling and harrowing, the current I and the voltage U of the power system were measured. The recorded values were used to assess the draft power of the UGV.

RESULTS AND DISCUSSION

On Fig. 5 and Fig. 6, the results for the drawbar pull measurements for the passive miller and for the harrower are shown. For the sake of clarity, only two operating speed results are shown here (4 km $h^{-1}$and 14 km h^{-1}). The oscillating lines are fitted with linear trendlines which presents the mean drawbar pull. For both implements, typical values remain in the range of 4–8 kN. Note that as the implements are dragged, peaks occur, which are associated with implement getting stuck in the soil.

On Fig. 7, peak and mean drawbar pull values at different operating speeds are plotted. Note how the measurement data follows a polynomial (quadratic) dependence trendline. In this graph, two types of drawbar pull values must be distinguished:

1. 'Mean Operational Drawbar Pull' indicates the resistive forces measured during operation averaged over time.

2. 'Peak Operational Drawbar Pull' indicates the maximum force measured during the test. This short-term value provides an opportunity to optimally estimate mobility requirements.

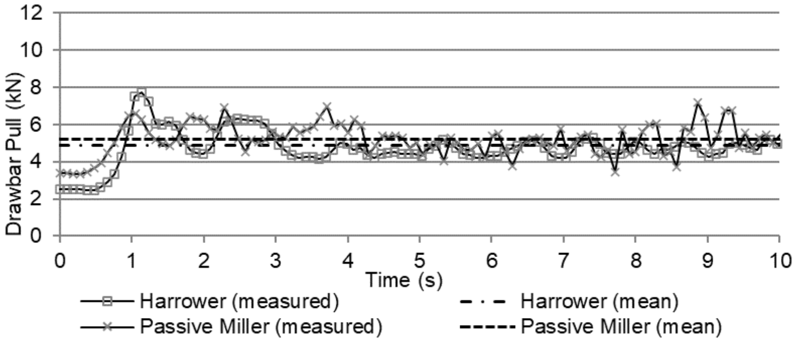

Figure 5. Measured and mean drawbar pull values for the passive miller and for the harrower at operational speed of 4 km h^{-1}. The oscillating lines (measured drawbar values) are fitted with linear trendlines which presents the mean drawbar pull.

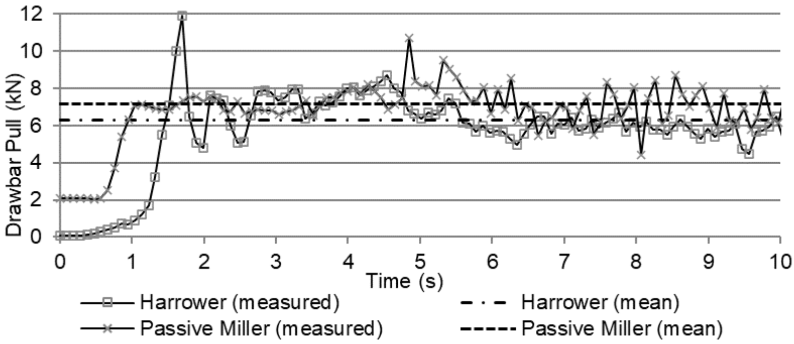

Figure 6. Measured and mean drawbar pull values for the passive miller and for the harrower at operational speed of 14 km h^{-1}. The oscillating lines (measured drawbar values) are fitted with linear trendlines which presents the mean drawbar pull.

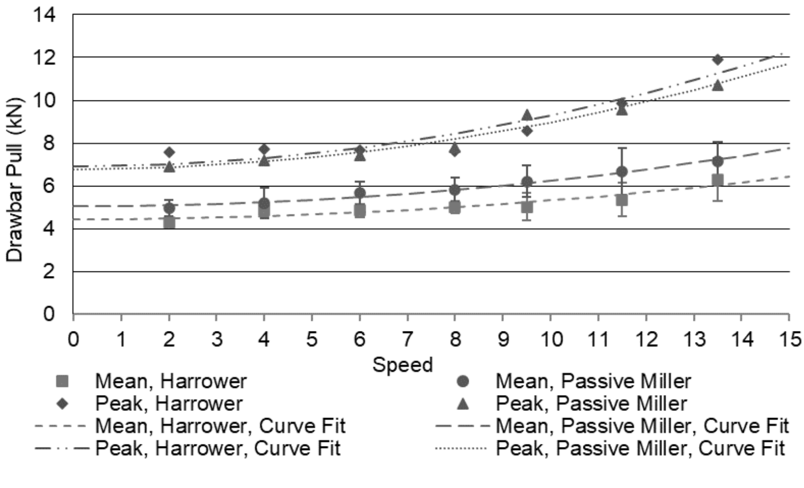

Figure 7. Mean and peak operational drawbar pull values for the passive miller and for the harrower at different operational speeds (km h^{-1}). Here, the dots present the measurement results (mean values) and the lines act as the polynomial curve fit.

Based on measured data (operational speed *v* and drawbar pull *F*), the drawbar power for a passive miller and for a harrower can be calculated. The calculated power consumption values are plotted on Fig. 8. In this graph, two types of drawbar power must be distinguished:

1. 'Mean Drawbar Power' indicates the power required during operation averaged over time.
2. 'Peak Drawbar Power' indicates the maximum power measured during the test. This short-term value provides an opportunity to optimally estimate power consumption requirements.

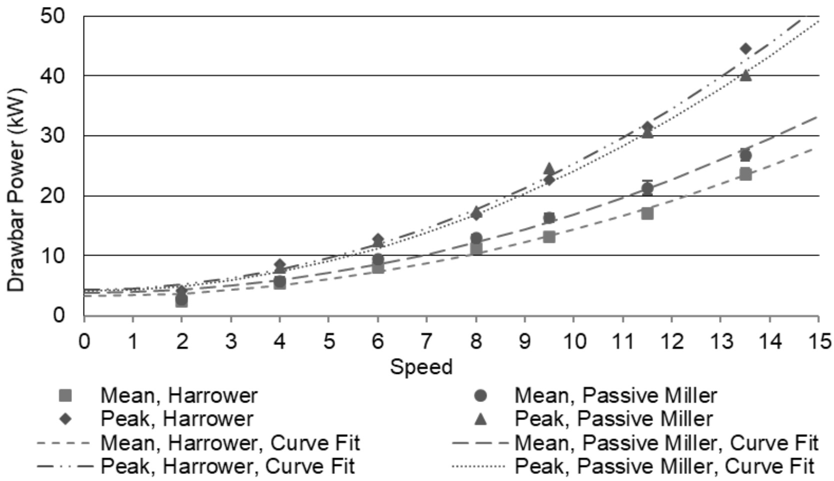

Figure 8. Mean and peak drawbar power values for the passive miller and for the harrower at different operational speeds (km h^{-1}). Here, the dots present the measurement results (mean values) and the lines act as the polynomial curve fit.

Based on measured data (current *I* and voltage *U* of the UGV power system), draft power of the UGV can be given (Figs 9 and 10).

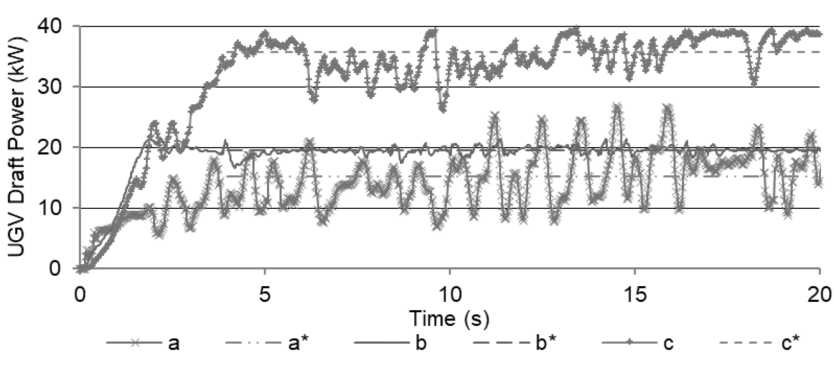

Figure 9. UGV draft power for the harrower. a) Speed 5 km h^{-1}; a*) speed 5 km h^{-1} with linear trendline 15.2 kW; b) Speed 8 km h^{-1}; b*) speed 8 km h^{-1} with linear trendline 19.5 kW; c) speed 14 km h^{-1}; c*) speed 14 km h^{-1} with linear trendline 35.8 kW.

The authors observed that the robotic system of interest capable of performing in peat extraction operations. No constraining slip was detected; the traction and power output of the UGV were found to be sufficient. Also, it was found that the readiness level of autonomous functions, such as 'Waypoint Navigation' and 'Remote Control' ('Teleoperation') are sufficient.

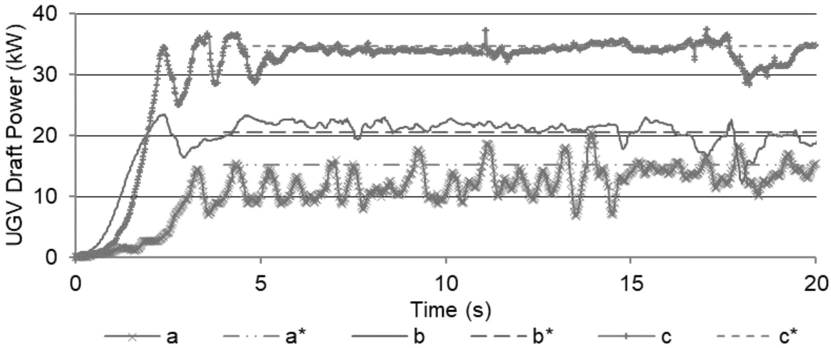

Figure 10. UGV draft power for the passive miller. a) Speed 5 km h^{-1}; a*) speed 5 km h^{-1} with linear trendline 14.2 kW; b) Speed 8 km h^{-1}; b*) speed 8 km h^{-1} with linear trendline 20.6 kW; c) speed 12 km h^{-1}; c*) speed 12 km h^{-1} with linear trendline 34.7 kW.

However, the energy storage capacity requirement was not met (Ueka et al., 2013). At lower operational speeds (up to 4–5 km h^{-1}), the UGV draft power was in a suitable range to perform long-term - the generator output matched the draft power of the implements. As the operational speeds increased (up to 14 km h^{-1}), the generator lacked the capacity to maintain sufficient power output to operate in the long run. To effectively operate in peat extraction operations, the energy generation and storage capacity must be improved.

To keep a steady operational speed, the passive miller must be towed with a higher draft force. As it turns out, for both implements, the required peak draft force is roughly the same. The oscillating behaviour is caused by two reasons:

1. Steering corrections (Moriwaki, 2005).
2. Uneven resistive characteristics of the soil which results the implement getting stuck for brief moments (Shahgoli et al., 2010).

Based on the test data, the use of an alternative powertrain can be proposed (Soltani et al., 2019). Most of the traction is provided by the main source of propulsion (diesel generator, battery pack and two electric motors). Additional power can be provided by a secondary power source (such as a 'fuel cell'). This would address the issue on energy storage capacity.

When comparing the data from Fig. 8, Fig. 9, and Fig. 10, then it is shown that the use of this UGV shows a promising outlook, since for all operational speeds and for both implements, the UGV draft power exceeds the required drawbar power in the near of 10 kW. This value corresponds to the idle running power of the UGV.

Given the restriction that unauthorised personnel have limited access to the peat extraction sites, the authors of this paper state that this robotic peat extraction system has the readiness level to be safely operated, thus making it close of entering the commercial market.

In summary, additional development for this robotic system is recommended with the main challenges identified as following:

1. The development of the 'Energy Generation and Storage Capacity' to effectively operate in peat extraction operations. Additional development of the system is recommended, to provide a full 8–12 h practical work time. It can be solved based on additional batteries (Solectrac, 2021) which would also increase the mass and influence the efficiency of the system; or based on fuel cell energetics which is commercially available for that kind of situation (Mekhilef et al., 2012; US Department of Energy, 2016; Papageorgopoulos, 2019; Ma et al., 2021).

2. The further development of autonomous functions such as the 'Waypoint Navigation System' (Kurita et al., 2017; Atyabi et al., 2018) the 'Obstacle Detection and Avoidance' (Kamel et al., 2020; Badue et al., 2021).

Furthermore, possible next steps are to add other implements to the robotic peat extraction system and to validate the results based on experiment data. As implements that do not require an external power supply were investigated in this work (harrower and passive miller), the next step would be to determine the capability of the robotic system using peat implements with an external power supply (e.g. an active miller). In addition to this, current measurement results are based on standard peat extraction implement solutions - no optimisation of existing implements is done here. Fundamentally, it would be possible to optimise the peat extraction implements (for instance, reduce the width of the implements N times), but this would require a separate analysis.

The concept of using the UGV in milled peat extraction is derived from the idea that the known mobility requirements (low ground pressure, terrain tractability, implement drawbar pull, power requirements) in the peat extraction industry match the capabilities of the robotic system of interest. However, it must be noted that this UGV is originally not designed for peat extraction. By now, the system lacks proper safety measures in terms of operating in an environment known for its fire hazards (Tissari et al., 2006). The authors suggest adding purpose-built spark arrestors to mitigate the subject.

CONCLUSIONS

In this study, the conventional tractor-based peat extraction system was replaced by an UGV-based system. The main difference comes from the fact that the human operator is removed from the wheel, which gives an opportunity to dimension the new system for peat field work. The current state of the robotic system of interest is such that it allows the test to be repeated in each peat field with a sufficient safety level, provided that no unauthorised persons enter it.

After the requirements and experimental data analysis, it was concluded that the robotic system under study can perform peat extraction operations (milling and harrowing):

1. The power characteristics of the robotic system of interest are suitable for the milled peat extraction implements tested in this experiment (harrower and passive miller).

2. The energy demand characteristics were found sufficient for lower operational speed (up to 4–5 km h^{-1}). However, at higher operational speeds (up to 14 km h^{-1}), the power supply capacity to effectively operate in milled peat extraction operations was found to be insufficient, thus requiring an improved solution.

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