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Outlining the mission profile of agricultural tractors through CAN-BUS data analytics

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

Published Version:
Outlining the mission profile of agricultural tractors through CAN-BUS data analytics / Mattetti M.; Maraldi M.; Lenzini N.; Fiorati S.; Sereni E.; Molari G.. - In: COMPUTERS AND ELECTRONICS IN AGRICULTURE. - ISSN 0168-1699. - ELETTRONICO. - 184:(2021), pp. 106078.1-106078.9. [10.1016/j.compag.2021.106078]

Availability:
This version is available at: https://hdl.handle.net/11585/832181 since: 2022-10-10

Published:
DOI: http://doi.org/10.1016/j.compag.2021.106078

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(Article begins on next page)

24 April 2024

This is the final peer-reviewed accepted manuscript of:

Michele Mattetti, Mirko Maraldi, Nicola Lenzini, Stefano Fiorati, Eugenio Sereni, Giovanni Molari,

Outlining the mission profile of agricultural tractors through CAN-BUS data analytics,

Computers and Electronics in Agriculture, Volume 184, 2021, 106078, ISSN 0168-1699,

https://www.sciencedirect.com/science/article/pii/S016816992100096X

The final published version is available online at:

https://doi.org/10.1016/j.compag.2021.106078.

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OUTLINING THE MISSION PROFILE OF AGRICULTURAL TRACTORS THROUGH CAN-BUS DATA ANALYTICS

Michele Mattetti[a*], Mirko Maraldi[a], Nicola Lenzini[b], Stefano Fiorati[b], Eugenio Sereni[c], Giovanni Molari[a]

[a] Department of Agricultural and Food Sciences, Alma Mater Studiorum – University of Bologna, viale G. Fanin, 50, 40127, Bologna, Italy

[b] CNH Industrial – Tractor Innovation Engineering, viale delle Nazioni 55, 41100, Modena, Italy

[c], viale delle Nazioni 55, 41100, Modena, Italy

[*] tel. +39 051 2096174, fax +39 051 2096178, email: *michele.mattetti@unibo.it*

Abstract

Tractor manufacturers need to know how farmers use their agricultural tractors for an optimal machine design. Tractor usage is not easy to assess due to the large variability of field operations. However, modern tractors embed sensors integrated into the CAN-BUS network and their data is accessible through the ISO 11783 protocol. Even though this technology has been available for a long time, the use of CAN-BUS data for outlining the tractor usage is still limited, because a proper post-processing method is lacking. This study aimed to present a novel classification scheme of CAN-BUS data which permits to outline the tractor usage. On a tractor, a CAN-BUS data logger and a GNSS receiver were installed, and real-world data were recorded for 579 hours. Thus, data was obtained in the most realistic condition. Tractor positions were classified using GIS layers while operating conditions were classified depending on the usage of the tractor's subsystems. The method highlights that showed to be able to detect the 97% of the logged data and that the tractor operated on the field in working, on idle, and moving duties for 65%, 18% and 16% of the time, respectively. The method allows a far more precise outline of tractor usage opening opportunities to obtain large benefits from massively collected CAN-BUS data.

KEYWORDS: data mining; Agriculture 4.0; CAN-BUS; real-world data; task classification

Table 1: Nomenclature

D_{OFF}	Distance travelled in out-of-work state	[m]
D_{ON}	Distance travelled in in-work state	[m]
$GNSS$	Global navigation satellite system	$[-]$
n_e	Engine speed	[rpm]
$n_{PTO,f}$	front PTO speed	[rpm]
$n_{PTO,r}$	rear PTO speed	[rpm]
P_e	Engine power	$[kW]$
RWI	Rear hitch in work indication	$[-]$
T_e	Actual engine-percent torque	[%]
T_f	Nominal friction-percent torque	[%]
T_H	Headland turns duration	[s]
T_r	Engine reference torque	[Nm]
V_t	Tractor ground speed	$[km\ h^{-1}]$

Introduction

The typical usage of a tractor model is described through its mission profile, which is a synthetic description of a tractor use. Mission profiles report the factors that influence the operational durability of tractor components (Johannesson & Speckert, 2013). A mission profile may report:

- the typical tractor service life;
- the typical contribution of each operating modes on the service life (e.g. ploughing, on-road, and off-road transportations, etc);
- how each component is typically used (e.g. the input power and speed on gearboxes, vehicle ground speed, etc).

Mission profiles are essential for a proper design/selection of tractor components (Sehab et al., 2011) or for designing durable and reliable machines with an optimal balance between under-designs and over-designs (Plaskitt & Musiol, 2002).

Mission profiles of agricultural tractors include several factors, and these factors make their mission profile estimations much more challenging than that of road vehicles. Indeed, a road vehicle may travel on only three different types of roads (e.g. highway, city, country road) and two types of load levels (the driver alone and with 4 passengers and luggage) (Marchesani et al., 1992); on the other hand, row crop tractors may be used for a larger variety of uses (e.g. road transportation, soil preparation, sowing, haying, etc.), and each can be accomplished at different load levels due to the different ground conditions.

To estimate a mission profile, tractor usage from a sample of farmers is necessary. This is typically carried out through surveys aimed at obtaining information about the farm size, yearly usage of tractors, list of farming operations carried out in the farm, and how each operation is performed (Mattetti et al., 2012). This approach is usually adopted for its easiness in obtaining data from large samples, but the obtained information is biased toward subjective judgements, which could lead to unreliable mission profiles. A different approach consists in installing switchboards inside tractor cabs (Paraforos et al., 2017) or through specific smartphone apps (e.g. 365Farmnet) which allow farmers to assign the task they are accomplishing with the tractor. However, these approaches require a manual effort of farmers, who may forget the task assignment.

In modern tractors, the operating parameters of all the tractor subsystems can be monitored using CAN-BUS technologies together with SAE J1939, and ISO 11783 protocols (ISO, 2012; Molari et al., 2013; SAE, 2006). In previous studies, CAN-BUS messages were successfully used to outline the usage of specific tractor components (Mattetti et al., 2019), to determine field efficiencies of agricultural machinery (Pitla et al., 2014, 2016) or to monitor specific tractor operating modes (Molari et al., 2019). The best approach for a proper mission profiling would be recording and analysing real-world CAN-BUS data of a large fleet of tractors. In this way, the recording process would not interfere with farming activities and data would be recorded in the most realistic conditions. But then, the environment where vehicles operate is unknown, and advanced classification approaches are essential for a reliable estimation of the mission profile (Fugiglando et al., 2019). Data classification is the process of grouping together portions of signals related to the same work state (Zhang et al., 2017). A sort of data classification is already provided by telemetric data service supplied by each tractor manufacturer (New Holland MyPLM Connect, John Deere JDLink). In these tools, the work states are defined on the basis of simple threshold-rules, in other words a work state is defined when any signal exceeds a threshold. For example, in telemetric data services, tractors are:

- on fieldwork state when the three-point linkage is down, but farmers may drive bare tractors on the field with the three-point linkage in the down position.
- on moving state when its speed exceeds a threshold specified by the driver (i.e. 25 km h^{-1}), but the proper value may change in function of the road state (i.e. presence of speed humps, road damages, etc).

For these reasons, this approach is far too simplistic and data misclassifications are not infrequent. More advanced rule-based algorithms were proposed for specific tractor operations (Ettl et al., 2018), and forage harvesters (Harmon et al., 2018; Zhang et al., 2017). Rule-based algorithms require knowledge from the experts and a reasonable amount of effort to design and implement effective rules for real-world data. Indeed, in real-world conditions, tractor operativity may change according to a variety of operating conditions (in terms of soil, implement type, driving style). Thus, for outlining the tractor usage, a robust and flexible method must be developed, which can deal with the variability induced by the variability of tractor manoeuvres (Mattetti, Molari, et al., 2017).

This article aimed to develop a robust and automatic classification scheme able to identify the tractor mission profile using real-world CAN-BUS, and trajectory data.

Materials and methods

Data acquisition

The analysis was applied to a New Holland T7 tractor (CNH Industrial N.V., Amsterdam, NL) whose specifications are reported in Table 2. This was chosen because tractors of this class are rich in terms of embedded sensors allowing for comprehensive monitoring of the activity of the different embedded subsystems.

Table 2 – Specifications of the tractor used in this study.

Maximum engine power	(kW)	198
Engine displacement	(m^3)	6.728
Number of cylinders	(–)	6
Engine tier	(–)	4B
Transmission	(–)	Continuously variable transmission
Number of auxiliary hydraulic valves	(–)	4
Three-point linkage	(–)	Rear
PTO	(–)	Front and rear

The tractor was in use between the June 2018 and October 2019 by 5 professional drivers with more than twenty years of experience. The tractor was used in the Agricultural Farm of the University of Bologna. The size of the farm is 500 ha, where 67%, 10% and 23% of the land are devoted to cereals, orchards, and haying, respectively. The farm is distributed in three different units (i.e. areas where tractors are stored overnight) located in three different towns; the farther locations are 35 km apart. In this farm, this tractor is mostly used for transportation tasks and primary and secondary tillage tasks.

A stand-alone CAN-BUS data-logger optimised by CNH Industrial was installed on the tractor. The data-logger was set up to automatically record all the CAN-BUS messages anytime the tractor engine was turned on so that the recording process did not interfere with farming activities. In particular, the CAN-BUS data logger is equipped of two separated CAN-BUS channels compatible with the standards: SAE J1939-14 (SAE, 2016a) and SAE J1939-15 (SAE, 2018b). The data-logger embeds a BLE (Bluetooth low energy) scanner which scans the BLE beacons in its surroundings (up to 10 meters) every second. Commercial BLE beacons (Mokosmart M1 Beacon, Shenzen, China) were attached to the implements available at the farm as suggested in other studies (Calcante & Mazzetto, 2014) (Fig. 1).

Fig. 1: A trailer used during the project. Enclosed in the yellow circle, a BLE beacon that permitted the identification of the trailer.

The BLE scanner records the identifiers of the detected BLE beacons to record implement connected to the tractor. Moreover, a Garmin Dash Cam 55 (Garmin Ltd., Olathe, KS, USA) was installed on the windshield of the tractor to document the tractor activity in order to ensure the reliability of the classification scheme.

For the purpose of this study, only signals with the following Suspect Parameter Numbers (SPNs) and Parameter Group Numbers (PGNs) (ISO, 2012; SAE, 2013) were used for the analysis:

- SPN 544 and PGN 65251: "*Engine Reference Torque*" that reports the torque as a percent of Engine Reference Torque (SPN 544 and PGN 65251) and it is denoted as T_r in the following.

- SPN 513 and PGN 61444: "*Actual Engine - Percent Torque*" that reports the torque as a percent of T_r , and it is denoted as T_e in the following.
- SPN 513 and PGN 5398: "*Nominal friction-percent torque*" that reports the frictional and thermodynamic loss of the engine itself, pumping torque loss and the losses of fuel, oil and cooling pumps as a percent of T_r, and it is denoted as T_f in the following.
- SPN 190 and PGN 61444: "*Engine Speed*" that reports the revolution speed of the engine crankshaft, and it is denoted as n_e in the following.
- SPN 1883 and PGN 65090: "*Rear PTO output shaft speed*", that reports the speed of the rear PTO.
- SPN 1882 and PGN 65090: "*Front PTO output shaft speed*" that reports the speed of the front PTO.
- SPN 1877 and PGN 65093: "Rear hitch in-work indication " that reports the rear hitch is positioned below (in-work) or above (out-of-work) 85% of the position of the rear three-point linkage (SPN 1873 and PGN 65093). This signal is denoted as RWI in the following.

Moreover, a GNSS (global navigation satellite system) receiver with an update rate of 10 Hz, with no differential correction, and with a claimed accuracy of 2.5 m (in terms of circular error probable) (IPESpeed, IPETronik GmbH, Baden Baden, Germany) was installed in the tractor to monitor its position and its tractor ground speed (V_t).

Data analysis

All the signals were interpolated at 10 Hz using a cubic spline so that the sampling rate of all the signals was the same. From the recorded data, the delivered engine power (P_e) was calculated as follows:

$$P_e = T_r \cdot \frac{T_e - T_f}{100} \cdot n_e \frac{2\pi}{60}$$

All the portions of the recorded signals acquired when the tractor position was not logged (because the GNSS receiver did not obtain a strong enough satellite signal, e.g. when the tractor was moved out from an indoor environment) were excluded from the analysis. Tractor positions were classified into three categories:

- $\boldsymbol{road}$, anytime the position was closer than 3 m to any road stretch. The 3 m threshold was chosen based on the circular error probability of the GNSS receiver used in this study. For a full automation of the process, this was carried out by checking if there is any intersection point between any road stretch and a circle, with a radius of 3m, centred in the tractor position.
- $\boldsymbol{field}$, anytime the position was inside the boundary of any field plot.
- $\boldsymbol{farm}$, anytime the position was inside the boundary of any farm unit.

For the classification of the tractor position, a shapefile containing the road network, the boundaries of field plots, and the boundaries of the farm units were created. The creation of the shapefile started by downloading the soil use and the road network from the geoportal of the Emilia Romagna region (*Dati preconfezionati — GeoER*, 2019). To this shapefile, the boundaries of three farm units were added.

The tractor operating conditions were classified into three categories: idling, moving, and three-point linkage use. Idling condition was defined as the state where the tractor was standing with no use of any PTO for more than 5 s; the duration threshold was added in order to not include portions where the tractor was temporary still during manoeuvring, like reversing the tractor direction at the headlands. *Moving* condition was defined as the state where tractor ground speed was greater than 0 km h^{-1} with no use of the three-point linkage or both PTOs. *Three-point linkage use* was defined as the state where the three-point linkage was used for field operations. This occurs anytime a sequence of a pass, headland, and pass was repeated. RWI signal shows a rectangular waveform, but when the tractor operates on field operations, repetitive pulses could be observed (Fig. 2 - right). A method for discerning field operations from implement hitching or machine moving activities was developed and it is described in the following.

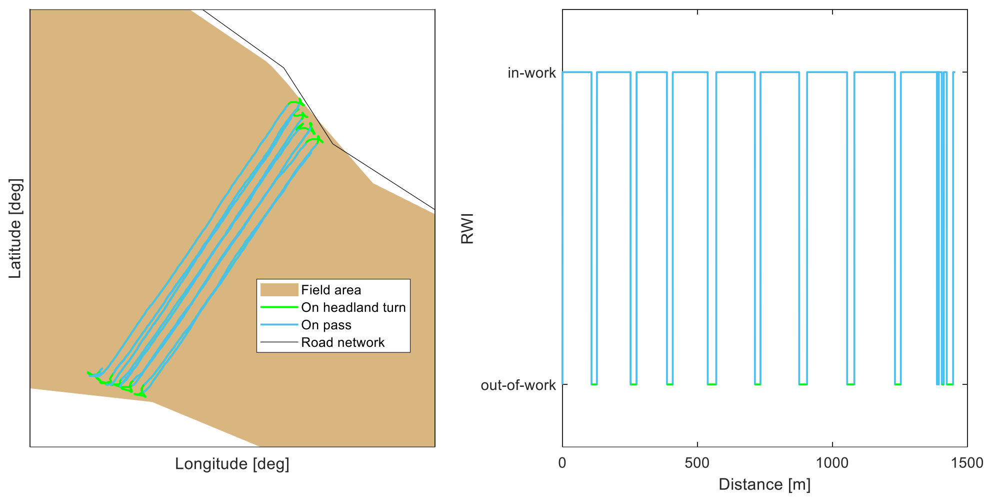

Fig. 2: Tractor trajectory (on left), and RWI signal (on right) during a field operation with a plough.

First, the distance travelled by the tractor on each in-work (D_{ON}) and on the out-of-work (D_{OFF}) states of RWI signal was calculated. For field operations, D_{ON} and D_{OFF} represent the length of passes and headlands, respectively. Both depend on several operating parameters like length of fields, and headland strategy (Paraforos et al., 2018). For field operations, D_{OFF} was usually included in a range between 1 and 70 m. Values of D_{OFF} below the lower bound occurred on implement hitching and values of D_{OFF} above the upper bound occur when the tractor switched from or to a moving operation. The above range was determined using the following approach:

- Identification of the portions where the tractor was operating in the field from video data collected with the camera.
- Extraction of all the logged signals in this portion.
- Calculation of histograms of D_{on} data of 1200 headlands and from it the threshold was set.

The algorithm started by calculating the series of D_{ON} and D_{OFF}, and *three-point linkage use* classification occurred in the timespan where D_{OFF} are included in the beforementioned range. When this classification occurs, the high levels of RWI described the passes, while the low levels of RWI described the headlands. Then, the headland duration was calculated as the time elapsed between the falling and rising edge of RWI signal when the tractor was in *three-point linkage usage*.

The work states were defined based on a combination of the classification of the tractor position and the tractor operating activity (Table 3).

Table 3 – Rule used for the work states which characterise the tractor use.

Work states	**Classified tractor position**	**Boolean operation**	**Classified tractor operating activity**
On-road moving	*Road*	*AND*	*Moving*
Off-road moving	*NOT(Road)*	*AND*	*Moving*
Field work	*Field*	*AND*	*three-point linkage use*
Idle@field	*NOT(Road)*	*AND*	*Idle*
Idle@farm	*Farm*	*AND*	*Idle*
Marginal	*Otherwise*		

The idling on road was included into *marginal* because its contribution is of minor importance to the entire idling (Molari et al., 2019).

An example of the classification of the work states is reported in Fig. 3. One can note that in the first portion (in the first 6 min of the time histories) the tractor was classified as on-road moving task; indeed, the tractor was running at around 40 km h^{-1} and P_e was on average low with peaks when high tractor accelerations occurred. On the other hand, the last portion (from 13 min) was classified as field work, indeed V_t was lower than 10 km h^{-1} and P_e is close to engine limit.

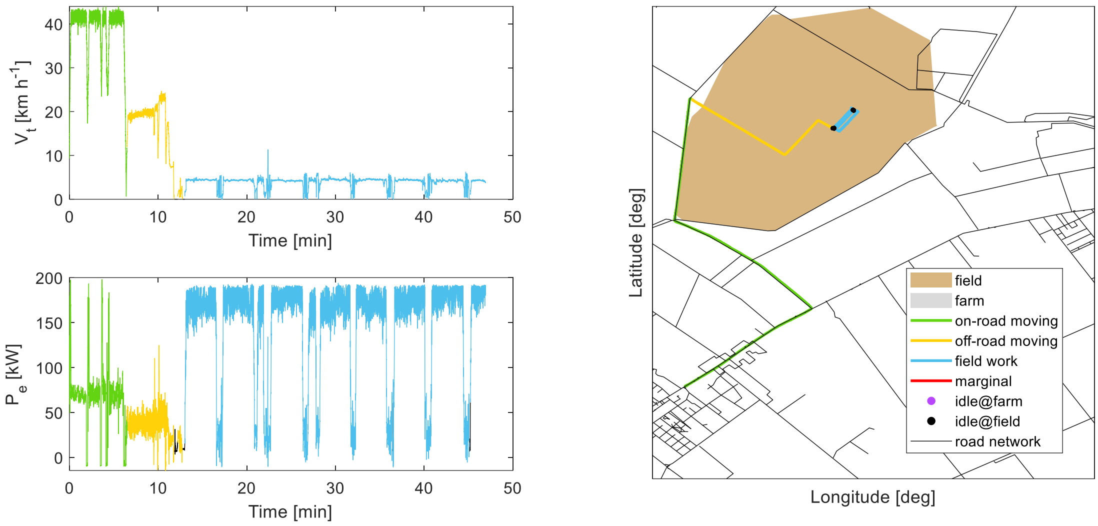

Fig. 3: Classification example of tractor ground speed (on the top left) and engine power (on the bottom left) compared with the tractor trajectory data (on right).

In this article, a task was defined as the portions where neither work states nor hitched implement was changed. For each task, the average values of all signals were calculated; for the subsequent dataset, outliers (i.e. misclassifications) were identified through the confidence ellipse method. This method consists of computing the confidence ellipse between two variables and considering outliers data points falling outside the confidence ellipse (Hodge & Austin, 2004). For drawn implements, the two variables were V_T and P_e (Fig. 4); as the power demand of this type of implements is mostly dependent on the working speed (Mattetti, Varani, et al., 2017), while for PTO-driven implements, the two variables were $n_{PTO,*}$ (* stands for f for front mounted implements and r for rear mounted implements) and P_e, as the power demand of this type of implements is dependent on the speed of the PTO (Balsari et al., 2020). The confidence level was set at 90%. A multivariate approach was necessary, since a low demanding ploughing may not be an outlier if the ground speed is low as well.

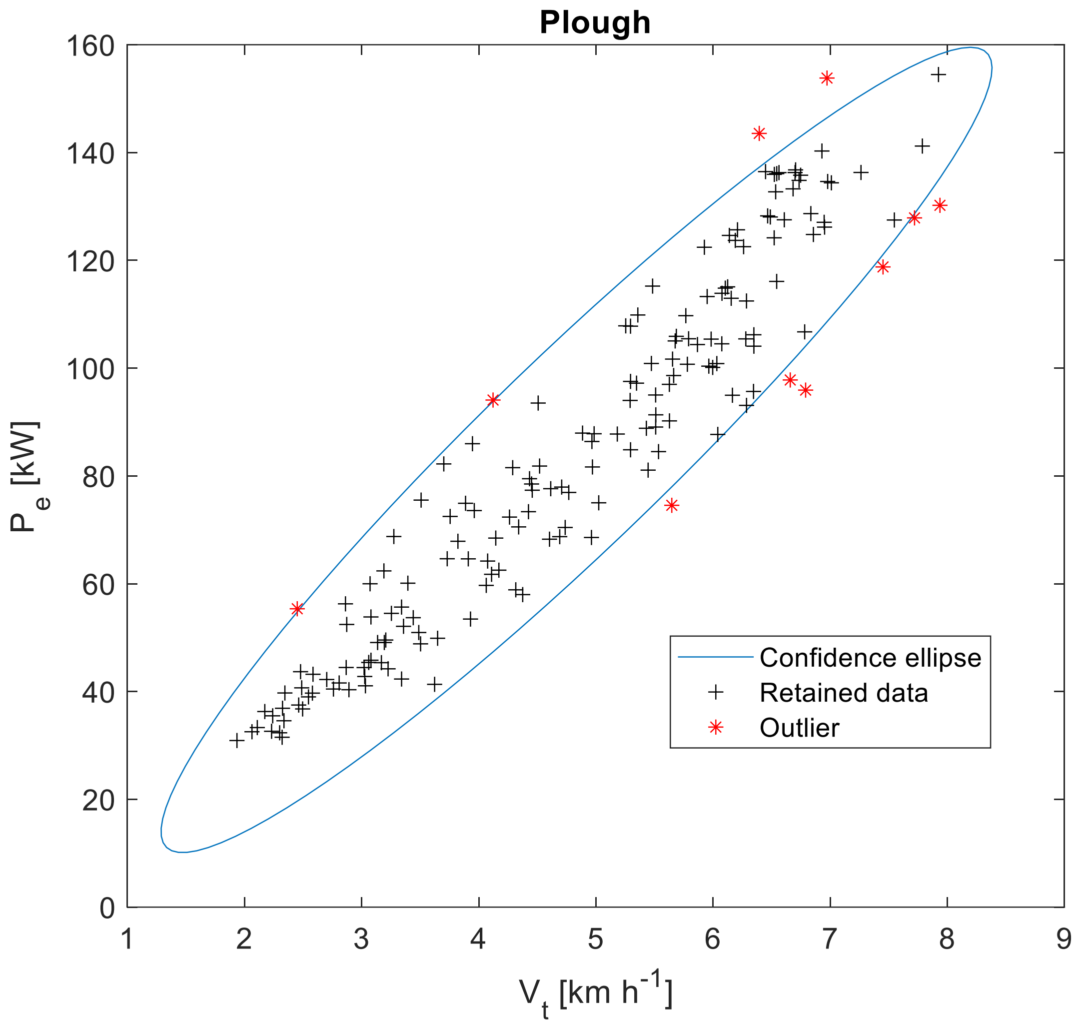

Fig. 4: An example of the outlier detection method for the field work tasks with plough. Only passes were considered.

Results and Discussion

The tractor was used for 107 days amounting to 579 hours overall. The tractor was used with 11 implements, but 5 of them were used for 84% of the time (Fig. 5). For 78% of the time, the tractor was used for ploughing, subsoiling, harrowing, and cultivating. Thus, the analysis was focused on the data related to those operations for the larger amount of available data. The tractor was used with no implement for 10% of the time, and in this configuration, the tractor was mostly moved from a farm unit to another.

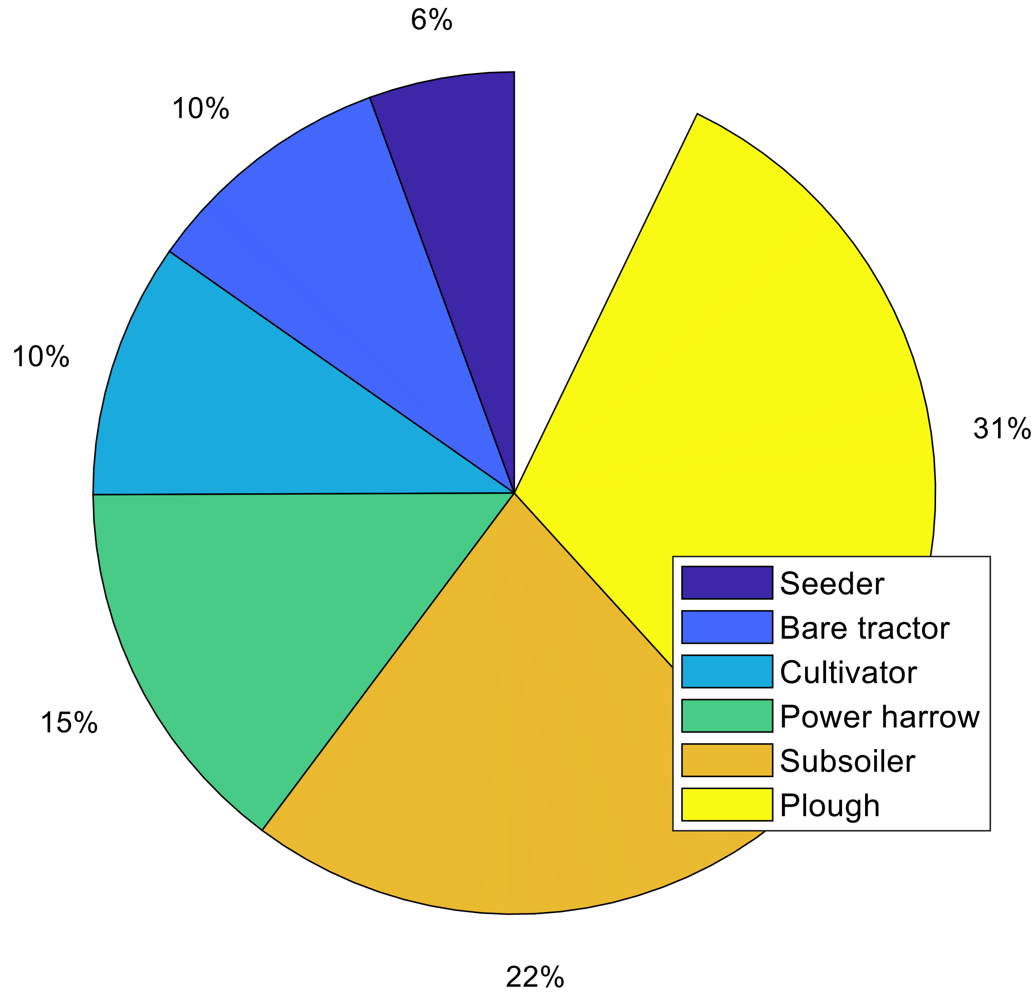

Fig. 5: Pie chart reporting the contribution of each implement on the operating time. In the chart, the implements used for less than 20 hours were not plotted for sake of clarity.

The tractor was used for field work tasks for 65% of the time and 18% of the time for idling activities (Fig. 6). The amount of idling is below the average value reported in the study by Perozzi et al. (2016) where the idling of a large sample of tractors was analysed.

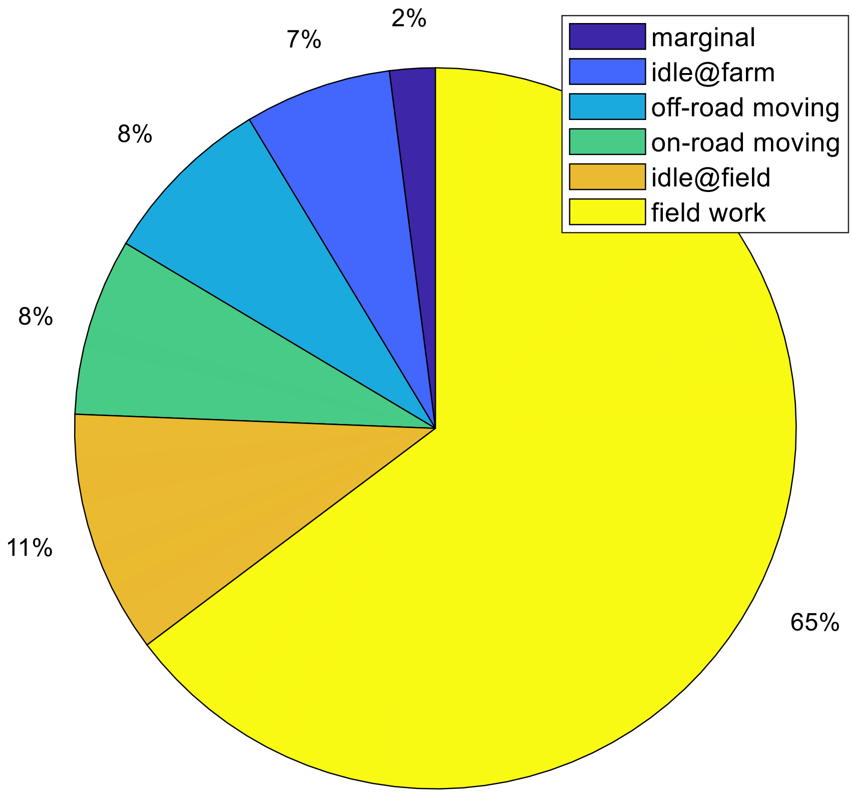

Fig. 6: Time contribution of each work state on the entire tractor activity.

The time contribution of *off-road moving* state is lower than that of the *on-roading moving* state. This is because the farm where the tractor was used is spread over a large area, which leads to infrequent but prolonged *on-road moving* states. Indeed, for *off-road moving* work state, the number of tasks are 38% of all the identified tasks and their average duration is 172 s. On the other hand, for *on-road moving* work states, the number of tasks are and 11% of all the identified tasks and their average duration is 478 s, respectively. The time contribution of *idle@field* work state is larger than that of *idle@farm* because the amount of idling stops on the field is much more frequent than those at the farm due to the varied source of stops, such as rest stops, driver turnover, checking the performance, removal of crop residual on implements (Hunt & Wilson, 2015). On the other hand, *idle@farm* state mostly occurs at the beginning and the end of the workday, and mostly for machine servicing or adjustment, implement hitching and machine parking (Molari et al., 2019). The sum of the time contributions for the *idle@field* and *field work* states provide an insight of the portion of time where the tractor operated for field related activities, and it includes the time for actual work, headlands, field setting, and maintenance at field (Lovarelli et al., 2017). Headlands contribute to 24% of the entire *field work* state and this figure is aligned to that of Ettl et al. (2018). Moreover, the time contribution of the *marginal* is less than 3%, which means that the defined work states can describe most of the tractor operations. In Fig. 7, the relative frequency of headland durations (T_H) for 10065 headlands is reported. T_H range from 3 s up to 230 s and it is strongly dependent on the headland patterns. 50% of the headlands ranged from 20 and 40 s and this result is aligned with that reported in other studies (Ettl et al., 2018; Paraforos et al., 2018).

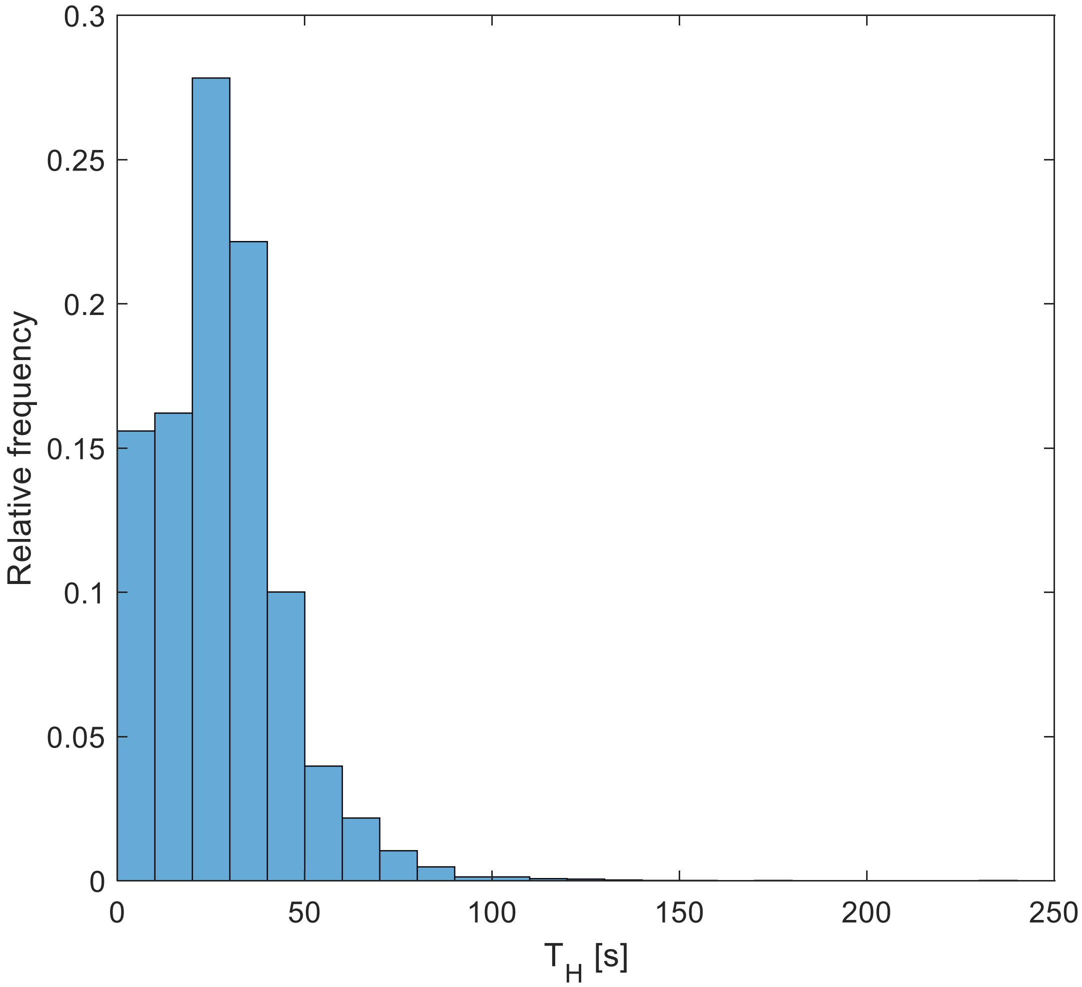

Fig. 7: Relative frequency distribution of the duration of the identified headlands.

Headlands shorter than 20 s are not infrequent, and they account for 32% of the headlands. These occur when the tractor worked around the field border where the circuitous turn strips at corner diagonals working pattern is adopted (Hunt & Wilson, 2015). In the most extreme cases, T_H is lower than 10 s, this occurs for an unconventional type of headland pattern. In particular, the farmer tilled two different fields separated by a country road and no turns can be observed in the tractor trajectory (Fig. 8). In the same plot, also headlands longer than 100 s can be observed, which occurred because the overlapping alternation pattern was adopted.

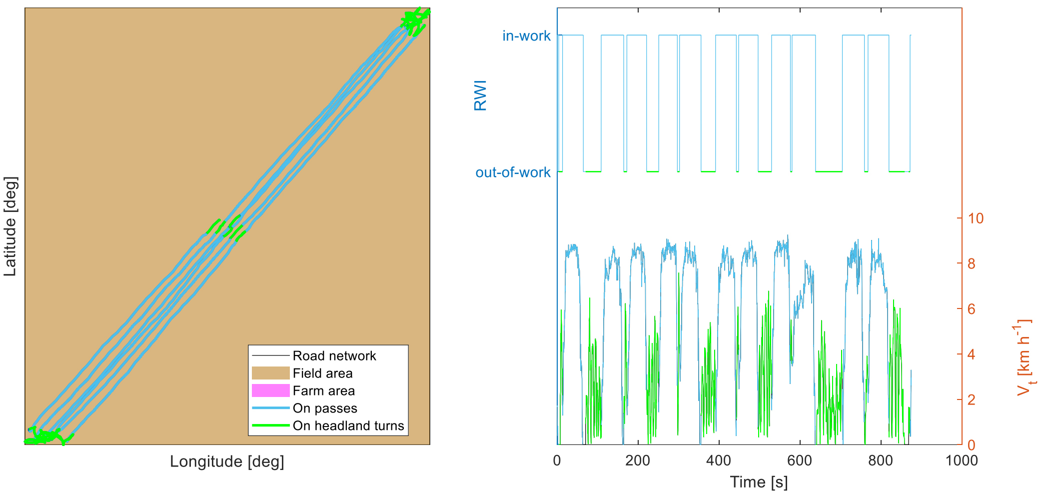

Fig. 8: Headland pattern where T_H was lower than 10 s and longer than 100 s.

The daily usage of the tractor ranges from 20 min to up 750 min; and the 50% of the days the tractor was used for more than 280 min (Fig. 9).

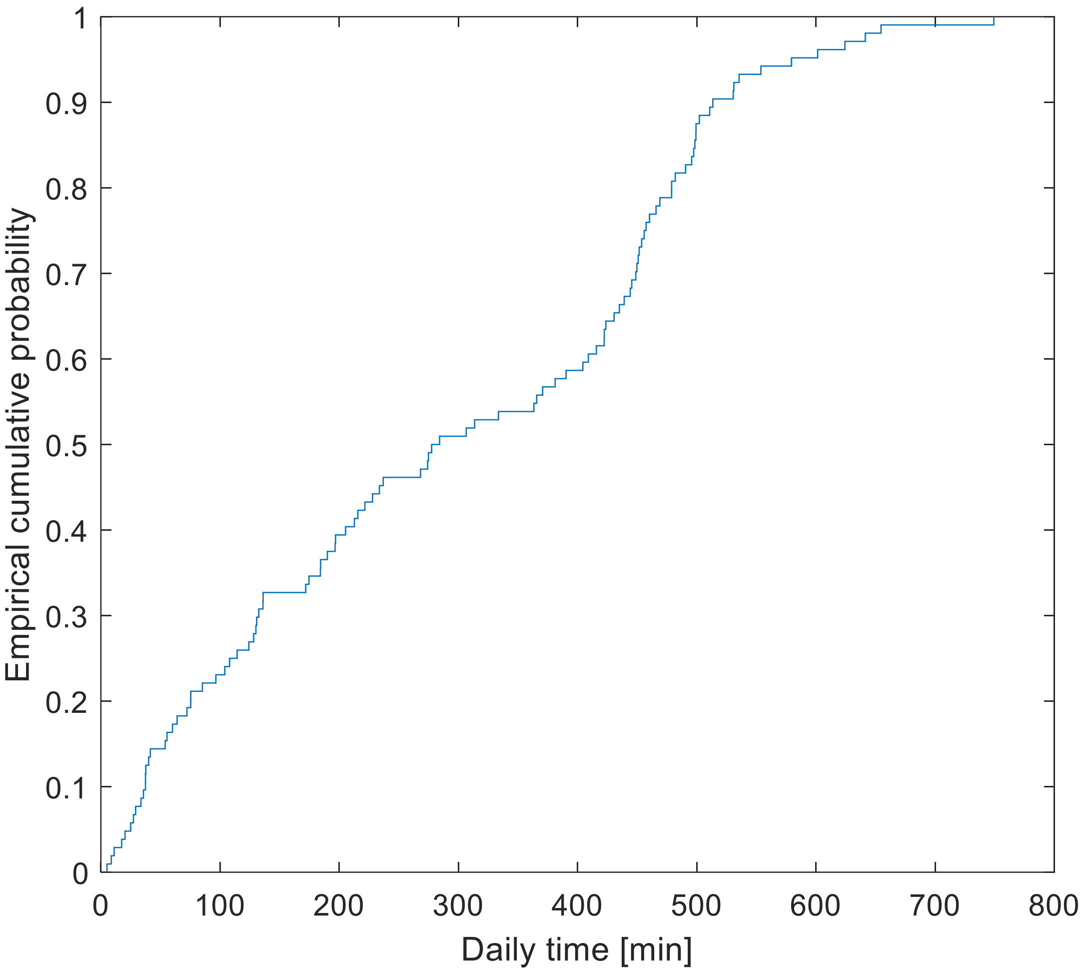

Fig. 9: Daily time of the tractor during the period of analysis.

In Fig. 10, a typical daily operating cycle of the tractor is reported. This is composed of the following activities:

1. tractor idling at the farm at the beginning of the day for implement hitching or, machine servicing and then moving the tractor from any farm unit to the field;
2. field work where idling stops may occur for field machine maintenance;
3. moving the tractor from the field to any farm unit.

When the driver turnover did not occur on field, or when changes in the tractor field operation occurred during the day. The afore-described cycle was repeated twice in a day since the driver went back to any farm unit for lunch or implement swapping.

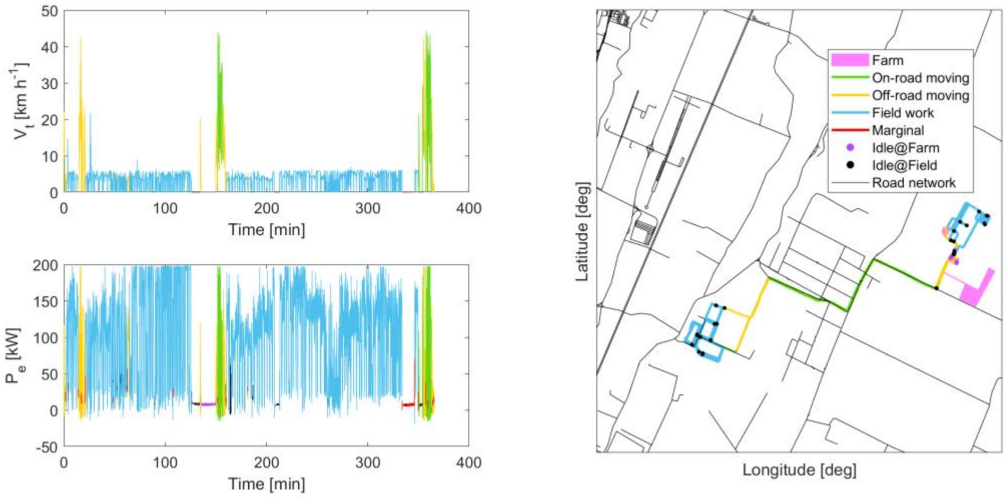

Fig. 10: Typical daily operating cycle of the tractor

In Fig. 11, the daily time contribution of the different tractor work states is reported. The largest contribution is provided by the *field work* state for 50% of the days, and it contributed to 73% of the entire daily activity. The other work states contribute less than 30% (without considering the outliers). The tractor was not used for field activities for 4 days since the daily time contribution of the *field work* state is 0%. In those days, larger contributions of the idling and moving states can be observed and the tractor was used for off-field activities because the weather conditions did not permit any field activities. Those activities consisted of machine servicing or moving implements from a farm unit to another. The results reported in other studies are aligned to the median values of the daily time contribution calculated in this study (Ettl et al., 2018; Kortenbruck et al., 2017).

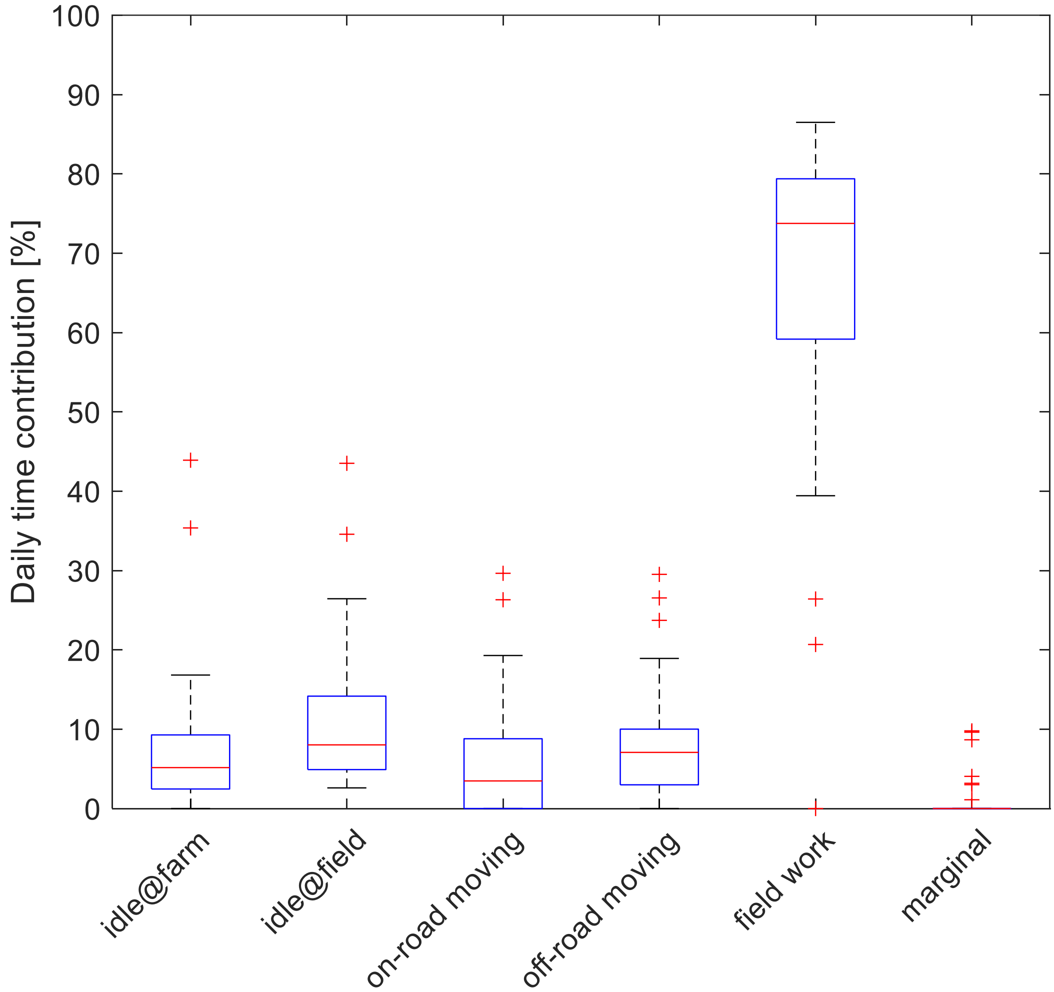

Fig. 11: Box-plot reporting the daily time contribution of the tractor work states. Red crosses correspond to the outliers.

The kernel smoothed probability distributions of V_t of the two moving states, and field work states with the four most frequent implements are reported in Fig. 12. All the distributions have unique modes except for that of the plough.

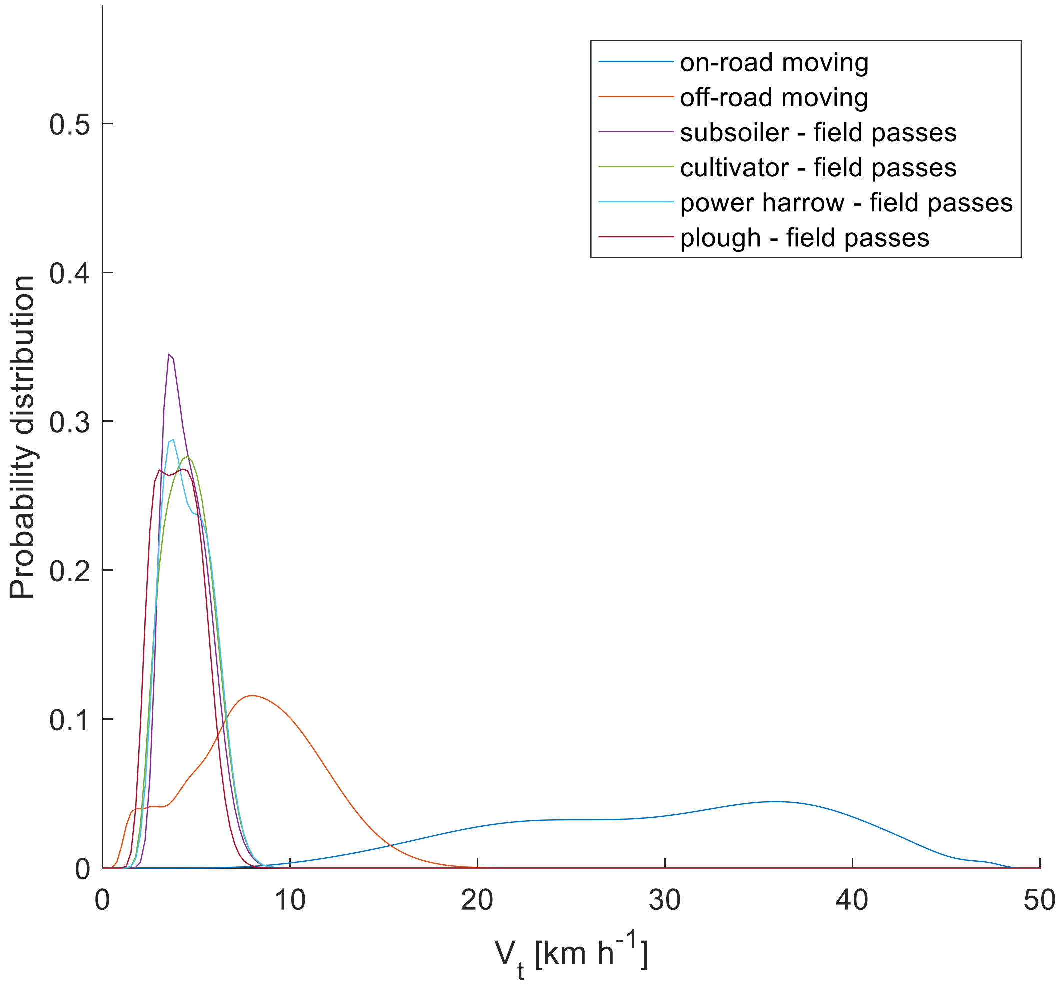

Fig. 12: Kernel smoothing distribution of tractor operating speed at various work states. Headlands were not considered on field operations.

In order to compare the distributions obtained in this study with those reported in the ASAE D497.7 (2011), the 10th and 90th percentiles, and the modes are reported in Table 4.

Table 4 – Main statistics of the speed distributions

Tractor states	**10th percentile [km h^{-1}]**	**Mode [km h^{-1}]**	**90th percentile [km h^{-1}]**
on-road moving	20.0	36.0	40.0
off-road moving	3.5	8.0	12.4
subsoiler - field passes	3.3	3.5	5.8
cultivator - field passes	3.0	4.2	6.0
power harrow - field passes	3.2	3.7	5.9
plough - field passes	2.6	3.0 / 4.2	5.5

The speed values observed in this study are slightly lower than those reported in the ASAE standard. For example, according to the ASAE standard, the speed range of a mouldboard plough is between 5 and 10 km h^{-1}, whereas it was found to be between 2.6 km h-^{1} and 5.8 km h^{-1} in this study. This difference may be because data in the ASAE standard is based on data collected in the US, where tractors and fields larger than those available in the farm used in this study.

The *off-road moving* distribution is overlapped with the distributions of the *field work* states for V_t lower than 8 km h^{-1} (which corresponds to the 48th percentile of its cumulative distribution), and it is overlapped with the distribution of *on-road moving* state for V_t higher than 12 km h^{-1} (which corresponds to the 85th percentile of its cumulative distribution). This highlights that discerning the moving states only using a threshold-rule for the speed, as it is usually done with many commercial telemetric data services, may lead to misclassifications.

In Fig. 13, the confidence level ellipses reported for three work states demonstrate that to fully discern the work states, a multivariate approach is necessary. The ellipses are clearly separated with only minor overlaps occurring between the ellipses of both moving work states, and between the ellipses of *field work* and *off-road moving* work states. V_t is strictly related to P_e depending on the type of the work state. Indeed, on *field work* tasks, the tractor is usually used with high engine loads, low speed and low gear ratios; while for moving tasks, lower engine loads and longer gear ratios are typically used with, high engine loads are limited to acceleration events only. For both moving tasks, P_e increases with V_t, due to the fact that the main resistance forces are the motion resistance which increases with the ground speed (Wong, 2001). The variability of V_t and P_e inside each operating condition depends on several factors, including driving style, operating, and environmental conditions. Indeed, P_e ranges from 23 kW up to 143 kW for the field work state on passes. Through a visual inspection of the recorded video, it was observed that the tillage operations carried out at low ground speeds (below 3 km h^{-1}) occurred because the soil was severely covered by crop residuals. In these conditions, farmers preferred to work slowly to avoid that the implement could get clogged with crop residuals, which could force the farmer to stop at headlands for implement clearing.

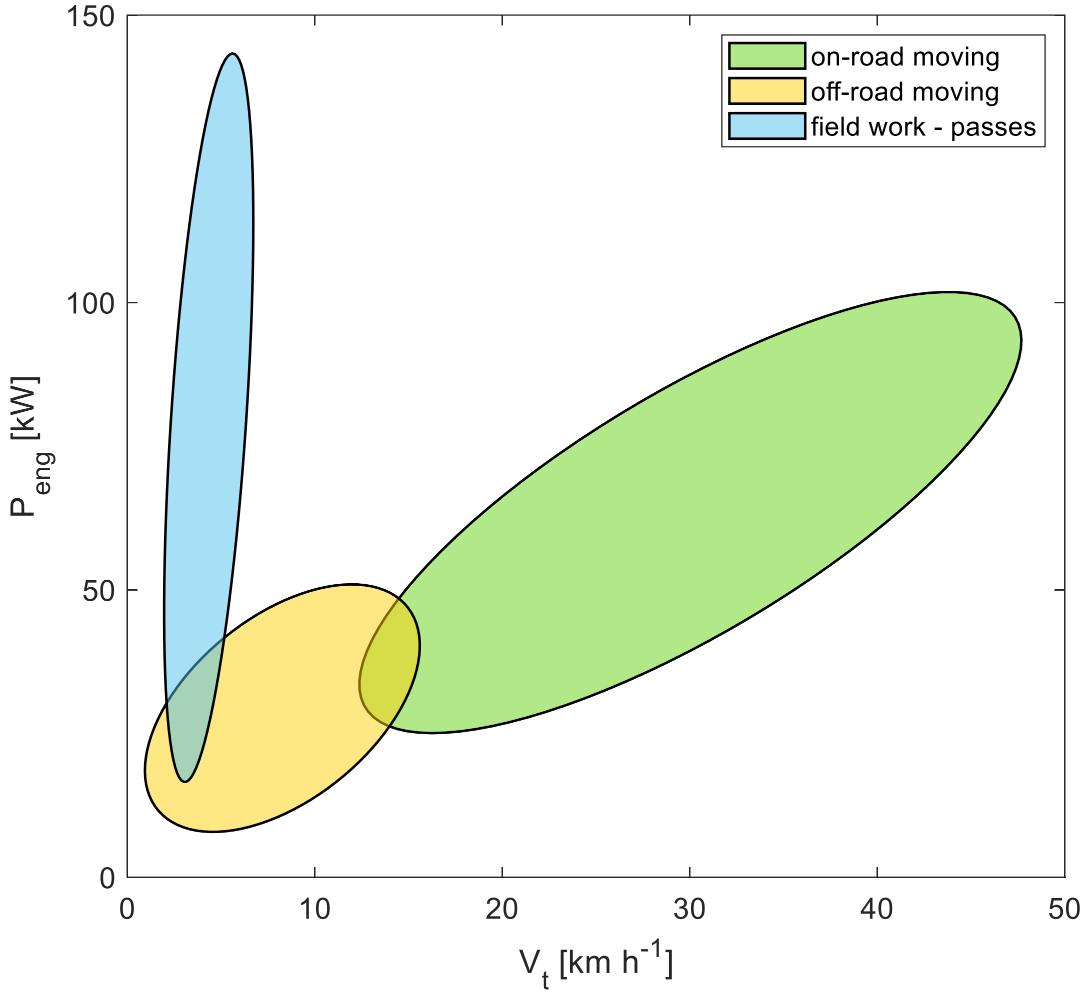

Fig. 13: Confidence level ellipses for three non-idling operating states.

Discussion

Few studies reported algorithms for classifying CAN-BUS data of agricultural tractors, and in all of them, results are based on limited datasets, not collected in real-world conditions. The strength of the classification scheme introduced in this study is the combined use of CAN-BUS, trajectory, and geographical data. This allowed to obtain a finer description of the tractor usage.

Indeed, tractor movements were classified based on the road type (i.e. on-road and off-road). On other similar studies, these two operating activities could not be distinguished because the method relies only on CAN-BUS, and trajectory data. Indeed, Kortenbruck et al. (2017) discriminated field from moving activities by evaluating the pattern of the tractor trajectory, which was that of a field operation if parallel traces not further apart than the implement width could be observed. The algorithm is not fully automatic because farmers have to input implement widths, but CEPs of non-RTK- GNSS receivers are of the same order of magnitude of typical implement widths. Thus, field operations cannot be reliably detected only with tractor trajectories. Paraforos et al. (2018) detected headlands and field passes from trajectory data, in particular, headlands were recognized when 180° overturns of tractor heading angle were identified. However, tractors do not always overturns of 180° on headlands especially when tractors work along the field contours (Fig. 8 – left). In Ettl et al. (2018), headland turns were recognised by setting the threshold of the duration with the three-point linkage is fully up position; however, the duration limit is dependent by the headland patterns (Paraforos et al., 2018), and idling stops can be frequent during headlands (Molari et al., 2019) (Fig. 10 – right).

The approach for recognising the field operations adopted in this study is based on the repetitive pattern of the RWI signal when tractors operate on field. This approach does not rely on any threshold values of any CAN-BUS parameter, this makes it more effective in dealing with real-world data. Setting the proper thresholds is a critical task because operating parameters may change depending on the type of implement, soil conditions, ground slope, and driving style (i.e. toward productivity or efficiency). The approach used in this paper works only with mounted and semi-mounted implements where a variability on the RWI signal can be observed, but the same principle could be used with other signals (e.g. steering angle) where a repetitive pattern could be observed also with trailed implements.

Conclusions

Information on the usage of agricultural tractors is not well-documented and very often farmers, scientists, and engineers rely on handwritten logbook data. In this paper, a data acquisition system which facilitates the data collection on agricultural tractors, and a novel classification scheme were presented. The novelty of the data acquisition system is that it combines a CAN-BUS logger, a GNSS receiver and a BLE beacon scanner, thus the hitched implement could be recorded even if they are not ISOBUS compliant. Moreover, the novelty of the data analysis method is on the combined use of CAN-BUS, trajectory and geographical data which allowed to introduce a classification scheme more refined than those proposed in similar studies. Indeed, the kinds of tractor activities were classified into 5 states depending on the tractor operating condition and its position. Thanks to the proposed classification scheme, engineers may benefit from massively recorded real-world data in uncontrolled conditions, which may leverage their design method. Indeed, engineers may focus most of their efforts on optimising the most frequently used components; or they may extract the most relevant duty-cycle from a large dataset of real-world data (Bishop et al., 2012). The dynamic characteristics of front axle and cabin suspensions could be optimised in order to achieve the best balance between on and off-road performance based on the frequency of each moving state and of the most frequent operating speeds. Future work should focus on defining work states in greater details and adapting the classification scheme in order to analyse real-time CAN-BUS data. In this way, the algorithm could be embedded in in-vehicle computer systems and thus vehicle sub-systems could be controlled based on the actual work state. For example, parameters of tractor subsystems could be preventively set when the tractor is approaching a specific road type (i.e. on-road or off-road), and that could be especially useful for setting the damping coefficient of semi-active suspensions or the tyre pressure if the tractor embeds central tyre inflating system.

Acknowledgements

This project was supported within the PRIN national framework by MUR (Ministry of University and Research), notification 2015 "Optimization of operating machinery through analysis of the mission profile for more efficient agriculture" Grant number: 2015KTY5NW.

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