

Article

Profiling the Instantaneous Power Consumption of Electric Machinery in Agricultural Environments: An Algebraic Approach

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Received: 17 January 2019; Accepted: 4 April 2019; Published: 10 April 2019



Abstract: One of the upcoming challenges in precision agriculture is the development of electric machinery able to replace traditional combustion engines. This step toward green agriculture practices still has to face the lifetime of the batteries. Despite their technological advancement, batteries' charges do not last as long as fueled engines. The route planning problem (RPP), for example, has to be re-thought according to the available energy resources since the machinery might exhaust its power without finishing the route. This work focuses in part on such a vast problem by proposing and testing an algebraic, yet simple technique to obtain instantaneous power consumption (IPC) profiles to be used by the RPP. The technique presented herein uses the knowledge of the terrain, the kinematic and dynamic constraints of the vehicle, and its electric model. The methodology followed is later validated in a real grove—i.e., trees cultivated in rows—showing that our power profiling technique reaches errors smaller than 10% when estimating the IPC and the associated energy required. This result can lead to better decisions by the farmer.

Keywords: green agriculture; electrical machinery; route planning

1. Introduction

The use of electric machinery (EM) in agriculture, specifically in precision agriculture, started to attract the attention of manufacturers in the last decade, especially motivated by the search for alternative energy sources to power machinery. In addition, green agriculture has become more important in precision agriculture practices due to its benefits to consumer's health [1–3]. Nevertheless, innovation in agriculture is not only related to electric machinery or power management, as pointed out in [4], where three innovation opportunities arose when including technology in the machinery: new safety systems to protect the driver, both in the vehicle and remotely; more comfort in the cabin for long working periods; and finally, the possibility of machinery working at a high speed (above 40 kmh^{−1}).

However, the use of EMs for agricultural applications is restricted to a number of tasks, as described in [5,6], such as harvesting, seeding, herbicide management, i.e., spreading, supervision and monitoring, and fruit phenotyping. In particular, on farms, EMs are used in assisting the seeding and harvesting process [7], either from an autonomous perspective (such as robotized EMs used for leveling agricultural terrain [8]) or non-autonomous, where a person drives the EM, performing tasks as a fueled tractor would (see [9,10] for further details).

Regardless of its function on the farm, an EM does not drive randomly. The motion of agricultural machinery is subject to the well-known route planning problem (RPP). The RPP, as stated in [11–14], is aimed at finding the way the machinery will traverse the agricultural environment according to its task. Thus, it should solve the problem of path planning (i.e., finding the route to follow), according to the machinery's own restrictions, both from its kinematics and dynamics. In particular, the works [15–17] showed several field cases in which the kinematic model of the machinery played a crucial role when entering or leaving a grove corridor, since its non-holonomic restrictions determine the allowed and forbidden maneuvers that the vehicle can perform, according to a previously-planned path. A path planning approach usually corresponds to a set of way-points that the vehicle should traverse (see [18] for further reading on path planning issues).

In addition to solving the route problem, the velocity of the machinery is also important. Velocity is usually related to energy [19,20], with time constraints related to the agricultural tasks. Hence, when moving, the vehicle is expected to fulfil its tasks within a previously-considered time interval [21]. Otherwise, latencies might affect agricultural production. A typical example is herbicide spreading: the spreader should traverse at a previously-set speed to ensure the appropriate chemical dispatch [7,13]. As in the previous case, regardless of the application, the machinery should have enough energy resources to accomplish the task.

In fueled machinery, energy autonomy is ensured for several hours, which might imply several hundred kilometers of autonomous navigation. In EM, autonomy is the same, but related to the battery's efficiency. Regardless of their technology, today's batteries in EM last only a few hours and are not comparable yet to fueled machinery [6]. In addition, the kind of terrain, its slope, and the deformation of the wheels, among other factors, have a direct impact on the electric energy usage. Thus, if for example an EM has ten hours of autonomy given by the manufacturer, if the mass changes as the vehicle travels (such as in the case of harvesting), such autonomy will decrease. A similar example can be found in herbicide tanks: as the machinery travels, the tank loses part of its mass during spraying. The velocity of the vehicle, moreover, has a direct impact on the power consumption, as will be shown later. Hence, the EM's speed will also constrain the autonomy of the vehicle [19]. However, if sustainable green agriculture is pursued, then the RPP problem must be re-thought, attending to the power consumption and energy usage of the vehicle.

This work is aimed at covering just part of the vast problem of having EM in agriculture. Since, as will be shown later, the instantaneous power consumption of the EM is directly related to the velocity of the vehicle, we propose an algebraic approach to profile the velocities of the EM and, thus, with a previous empirical model of the instantaneous power consumption (IPC) according to the terrain and wheel characteristics, to estimate beforehand the IPC and energy usage required by the RPP. It should be emphasized that this work does not focus on the RPP, but on providing an estimation of the IPC for a more efficient RPP strategy in agriculture, ensuring the achievement of the tasks by the EM.

2. Materials and Methods

Figure 1 shows the general architecture of the system implemented in this work for profiling IPC. Briefly,

- The EM consists of an automated golf cart, equipped with sensors and processors as described in Section 2.1.
- The EM is aimed at performing agricultural tasks, such as monitoring. The environment chosen is an experimental olive grove shown in Section 2.2. Nevertheless, the methodology presented here does not depend on the nature of the farm, since it can be either maize, soy, or avocados, among others.
- To characterize the IPC, current and voltage sensors are used as the vehicle interacts with the terrain and the environment. The modeling of the IPC is presented in Section 2.3, and the modeling of the energy in Section 2.4.

- Both the IPC and the energy assessment are used to provide an IPC and energy profiling technique, which is later used to improve the route planning problem, as will be shown in Section 2.5.
- Finally, a motion controller receives the directives from the RPP to drive the vehicle across the grove.

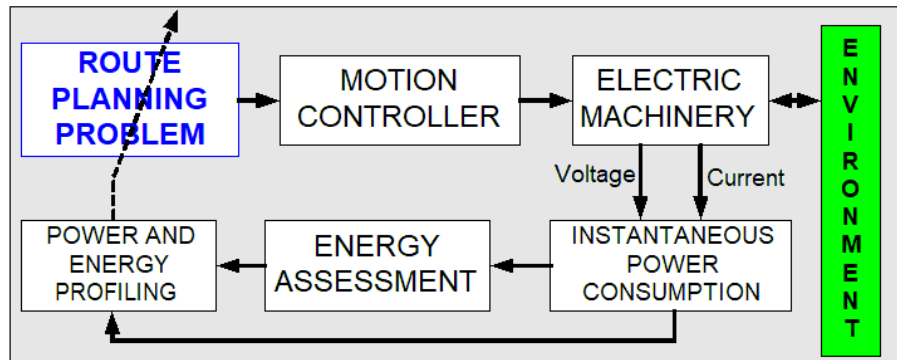


Figure 1. General architecture of the system.

Each stage from Figure 1 is explained in detail in the following sections.

2.1. Electric Machinery

The electric machinery used in this work consisted of an electric golf cart, Cushman Hauler Pro, automated for agricultural purposes, powered by 58 V (DC), reaching up to 45 kmh^{-1} of traction speed, and an autonomy of 100 km. Its heading was mechanical. In addition, it had an RTK (real-time kinematics), Navcom SF-3040, which had an accuracy of 0.01 m horizontal and 0.02 ms vertical. Its data rate was selectable from 1 Hz–10 Hz. It was mounted on the top of the vehicle, as shown in Figure 2. The batteries were connected to voltage and current sensors, thus measuring the output power of the batteries. The voltage range of the sensor went from 15 V–80 V, and the current ranged from -300 A – 300 A . An analog-to-digital converter of 12 bits was connected through a serial port to a GPU (graphics processing unit), Nvidia Jetson TX2, which processed the information from the RTK, the current and voltage sensors, and other artificial vision sensors connected to the EM—but not used for the purposes of this research—using ROS, a real-time robotic operating system.



Figure 2. Electric machinery: automated golf cart for agricultural applications.

In this work, we used the vehicle's encoders to estimate traction velocity and the RTK for geo-referencing the field trials. The sampling time of the system was set to 0.1 s, as the RTK was also set to work at 10 Hz. Synchronization among acquired data was achieved internally by the operating system checking the time stamp of each recording.

2.2. Agricultural Environment

Figure 3 shows a picture of the olive grove where the experimentation took place. The farm had a structured disposition corresponding to an experimental grove. Corridors were approximately 10 m in width and 100 m long. The terrain was a pressed clay type, leveled and flat.



Figure 3. Picture of the olive grove where the experimentations were carried out.

2.3. The Instantaneous Power Consumption

The IPC of an electric machinery can be calculated from the forces applied to the wheels [19,22]. As shown in Figure 4, a wheel might be subjected to rolling resistance, terrain unevenness, slippage, sinkage, aerodynamic resistance, and the wheel's own acceleration, among other factors. Assuming that traction is electric in the EM, but the heading is mechanical, then following the guidelines presented in [19,22,23], the resultant force on a wheel can be approximated, as shown in Equation (1).

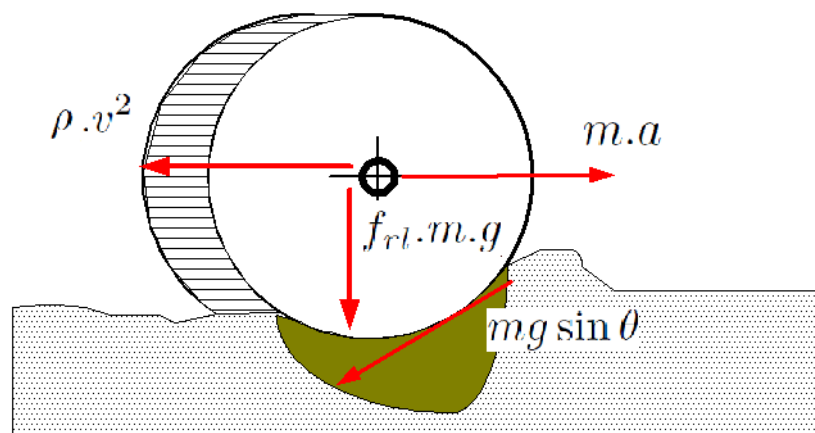


Figure 4. Forces acting on a wheel.

$$f_{wheel} = ma + f_{rl}mg \cos \theta + \rho v^2 + mg \sin \theta \quad (1)$$

The dot represents the scalar product; m is the mass measured at the contact point between the wheel and the terrain; g is the gravitational acceleration; θ represents the grade of the terrain; f_{rl} is the rolling coefficient; ρ is the aerodynamic coefficient (see [23] for further details); and v is the vehicle's traction speed. In the model shown in Equation (1), regenerative braking is not considered. In fact, Equation (1) only applies for non-deformable wheels, as stated in [19].

The mechanic power associated with the motion of the wheel is a function of the wheels' traction velocity (assuming no slippage), as shown in Equation (2):

$$P_{wheel} = f_{wheel}v = (ma + f_{rl}mg \cos \theta + \rho v^2 + mg \sin \theta)v \quad (2)$$

However, since such power (in Watts) results from the electric engine, we can call it output power. The input power, on the other hand, is the power delivered directly from the batteries of the EM. The input power can be calculated as $P_{battery} = \eta \cdot P_{wheel}$, where η is the efficiency of the system, expressed as:

$$\eta = \frac{P_{wheel} - I^2 r}{P_{wheel}} \quad (3)$$

where I is output current from the batteries and r is the resistance associated with all auxiliaries (see [19,23]) from the vehicle, such as lights, radio, and copper from the wires, among others. Since efficiency in Equation (3) can be known beforehand, we will focus only on the power consumed by the EM. Therefore, we have that the input power (also in Watts) can be written as shown in Equation (4), using Equation (2).

$$P_{battery} = \eta((ma + f_{rl}mg \cos \theta + \rho v^2 + mg \sin \theta)v) \quad (4)$$

In agriculture, machinery traverses at low speed compared to, e.g., urban navigation [21]. Thus, we can neglect the aerodynamic resistance from Equation (4). In addition, if we consider that the EM traverses a flat, not necessarily even, terrain, then the grade resistance can also be neglected. With these assumptions, the input power can be presented as:

$$P_{battery} = \eta((ma + f_{rl}mg)v) \quad (5)$$

In Equation (5), the output power is a function of the mass, velocity, and acceleration of the vehicle, as well as the rolling resistance. If the terramechanic parameters of the terrain do not change and also do not change the wheel characteristics (see [24] for further details), then f_{rl} in Equation (5) can be considered as constant. Therefore, $P_{battery}$ is a function of the vehicle's motion, i.e., velocity and acceleration, and its mass. In particular, the mass can change whether the vehicle loads or unloads crop.

2.4. Energy Assessment

From Equation (5) and knowing beforehand the sampling time of the system, we can measure the energy extracted from the battery in Joules. Let Δt be the sampling time of the system. Then, the energy extracted from the battery can be written as:

$$E_{battery} = \sum_{k=i}^{k=j} V_k I_k \Delta t = \sum_{k=i}^{k=j} \eta (ma_k + f_{rl}mg) v_k \Delta t \quad (6)$$

where in Equation (6), $k = i$ and $k = j$, with $j > i$, are any two time instants; V and I are voltage and current, respectively, directly measured from the battery using the sensors presented in Section 2.1.

2.5. Model-Based Power Profiles and the Route Planning Problem

The RPP concerns, among other aspects, the path planning or motion planning of the agricultural machinery, as stated in [12,15,16] (and the references therein). Velocity and acceleration are two of the RPP constraints that the machinery has to achieve to reach a previously-given position in the

workspace or to perform a previously-known task in a given time. The former is known as trajectory tracking or path tracking. Whatever the case, the RPP starts with a path planning approach, which can be defined as a set of way-points in the workspace over which the machinery should traverse. Figure 5 shows two paths with different way-point dispositions. In the first case (top), the distance among the way-points (red dots) is greater than in the second case (bottom). The machinery though starts at the same position in both situations. Since path planning is not the core of the research, we will assume that we already have a path planning strategy. For instance, works such as [16,18] can provide such a path for the RPP.

Once a path is determined, a trajectory tracking or path tracking control strategy is implemented to drive the EM through the farm. Examples of such control strategies can be found in [21] and the motion controllers implemented therein. As stated in [25], despite the motion control strategy adopted, the velocity of the EM directly depends on the distance among the way-points from the path. Thus, in Figure 5 (top), the distances among two consecutive way-points would cause a traction velocity of $v_\alpha \leq v_\beta$ (where v_β is the traction velocity for the path at the bottom of Figure 5 and v_α is the traction velocity for the path at the top). For an electrically-powered machine, the traction velocity can be kinematically modeled as shown in Equation (7).

$$\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix}^G = \begin{bmatrix} v \cos \phi \\ v \sin \phi \end{bmatrix} \quad (7)$$

where $\dot{x}$ and $\dot{y}$ are linear velocities according to some global coordinate frame G previously set; ϕ is the vehicle orientation, and v is the velocity control input. The model presented in Equation (7) is independent on the complete kinematic model of the vehicle, since only traction is considered (see [19]). If we consider Euler discretization, with a sampling time sufficiently small, we have that:

$$\begin{bmatrix} x \\ y \end{bmatrix}_{k+1}^G = \begin{bmatrix} x \\ y \end{bmatrix}_k + \Delta t \begin{bmatrix} v \cos \phi \\ v \sin \phi \end{bmatrix}_k \quad (8)$$

where k is the time instant and Δt is the sampling time, as in Equation (6). One of the main advantages of Equation (8) is that during Δt , it is assumed that v remains constant. Therefore, from Equation (5), we can remove acceleration a for the IPC, since v remains constant for each Δt . Thus, the IPC is a function of the mass (assumed constant herein, since the EM is aimed at farm monitoring only), the rolling resistance (also assumed constant), and the velocity.

To profile velocity, let us first assume that the vehicle is positioned at a given and known location in the environment, say $[x \ y]_k^T$ at time instant k . The goal then is to find the velocity v that could drive the EM from its current position to a desired one at time instant $k + 1$. However, such a desired position is one of the way-points previously planned by the RPP. Thus, we can re-write Equation (8) to incorporate the latter as:

$$\begin{bmatrix} x \\ y \end{bmatrix}_{ref,k+1}^G = \begin{bmatrix} x \\ y \end{bmatrix}_k + \Delta t \begin{bmatrix} v \cos \phi \\ v \sin \phi \end{bmatrix}_k \quad (9)$$

where the suffix *ref* refers to the desired position, which should be reached at the next sampling time, and it belongs to the reference path. Algebraically operating the above expression, we can find that:

$$v_k = \frac{1}{\Delta t} \begin{bmatrix} \cos \phi \\ \sin \phi \end{bmatrix}^{-1,*} \begin{bmatrix} x_{ref,k+1} - x_k \\ y_{ref,k+1} - y_k \end{bmatrix} \quad (10)$$

where in Equation (10), the asterisk stands for the pseudo-inverse of the matrix. Operating, we find that:

$$v_k = \frac{1}{\Delta t} ((x_{ref,k+1} - x_k) \cos \phi_k + (y_{ref,k+1} - y_k) \sin \phi_k) \quad (11)$$

Equation (11) shows the velocity profiled to reach the point $[x_{ref,k+1} \ y_{ref,k+1}]^T$ from the EM's position at $[x \ y]^T_k$ after one sampling time of Δt . It is to be noted that, to pursue the latter, a motion controller, as the ones presented in [21], should be implemented on the EM.

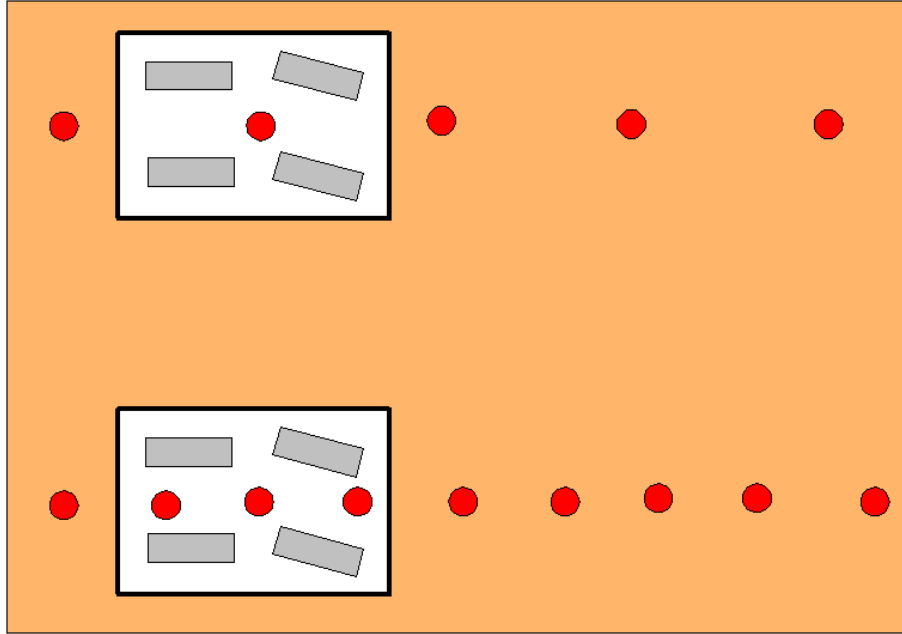


Figure 5. Velocity profiles: dependence on the route planning problem (RPP).

Finally, merging Equation (11) with Equation (5), with the assumptions made in this section, the IPC profiling can be expressed as:

$$\begin{aligned} P_{battery,k} &= \eta(ma_k + f_{rl}mg)v_k \\ &= \eta(ma_k + f_{rl}mg) \frac{1}{\Delta t} ((x_{ref,k+1} - x_k) \cos \phi_k + (y_{ref,k+1} - y_k) \sin \phi_k) \end{aligned} \quad (12)$$

where in Equation (12), the mass m and rolling resistance f_{rl} are assumed constants. If we also consider that v_k is constant during the period of a sampling time, then we can neglect the acceleration a to obtain:

$$\begin{aligned} P_{battery,k} &= \eta(f_{rl}mg)v_k \\ &= \eta(f_{rl}mg) \frac{1}{\Delta t} ((x_{ref,k+1} - x_k) \cos \phi_k + (y_{ref,k+1} - y_k) \sin \phi_k) \end{aligned} \quad (13)$$

Thus, Equation (13) shows the algebraic approach to profile the IPC, driven mainly by the traction velocity. Summarizing, to obtain Equation (13), the following assumptions were made: (i) the wheel is not deformable; (ii) the terramechanic parameters of the terrain do not change (thus, f_{rl} remains constant); (iii) as the EM traverses at low speeds, so the aerodynamic resistance was neglected; (iv) due to the sampling of way-points and the Euler approximation of the vehicle traction model, constant speed was assumed between any two consecutive way-points (following the guidelines previously published by the authors in [25]); (v) finally, η is assumed known beforehand, which is a very common hypothesis, as shown in [19]. Additionally, for the purpose of this work, we have implemented the RPP approach presented in [11], with some changes to adapt the RPP algorithm to the environment where the experimentation was carried out.

2.6. Re-Planning the RPP

One of the main advantages of having an IPC profiling strategy is that the RPP problem can be re-thought according to the remaining energy. To depict the problem, let us suppose the Ω is the path planned to be traversed by the EM. At some point $\xi \in \Omega$, an inner point of the path where the EM is positioned, one can estimate the energy needed to reach the end of the path using Equations (6) and (13). If the energy demanded to fulfil the path turns out to be higher than the one available in the batteries, then the EM will not be able to complete the task. Looking into Equation (13), it is possible to see the proportional relation between the IPC and the velocity. In particular, the higher the speed of the EM, the bigger the IPC. However, also, as the velocity increases, the time needed to fulfil the path decreases. Hence, if the available energy will not ensure that the EM will complete the path, increasing the EM speed might allow it. This is so, since Equation (13) is presented as a linear and static relation between speed and IPC, but as will be shown later, unmodeled effects change such situation. In other words, the available energy might not be enough to complete the path shown in Figure 5 (top) at v_α , but it might be able to complete it if the bottom path is used instead (with v_β), or vice versa.

Therefore, we propose the following searching criterion for path planning the RPP based on the available energy:

$$\begin{aligned} & \underset{\Delta x, \Delta y}{\operatorname{argmax}} P_{\text{battery},k} \\ & \text{s. t. } E_{\text{battery}}^\Omega > E_{\text{battery}}^{\text{available}} \end{aligned} \quad (14)$$

where $\Delta x = x_{\text{ref},k+1} - x_k$; $\Delta y = y_{\text{ref},k+1} - y_k$, $E_{\text{battery}}^\Omega$ is the energy needed to fulfil the path Ω , and $E_{\text{battery}}^{\text{available}}$ is the actual energy remaining in the battery system. Equation (14) can be seen as a searching strategy to find the best $[x_{\text{ref}} \ y_{\text{ref}}]^T \in \Omega$ to ensure that the EM will be capable of entirely traversing the previously-defined route. To do that, we take advantage of the model found to estimate and profile $P_{\text{battery},k}$ in Equation (13). The corresponding field trials are shown in Section 3.2.

3. Experimental Results

This section presents the results obtained during the field trials. First, the procedure followed to obtain a model of the IPC based on the velocity of the EM is shown. Secondly, the model is validated in several field trials in the olive grove shown in Figure 3.

3.1. Modeling the IPC

Since the mass and the gravitational acceleration from Equation (5) were previously known, the rolling coefficient remains unknown, which might vary according to the wheel's material, the terramechanic constraints, and the wheel deformation, among other several factors (see [24] for further details). In addition, despite the fact that we assumed flat and leveled terrain, rocks and small depressions might be found in the grove's corridor, causing spontaneous grade resistances. Thus, to obtain a model of the IPC with respect to the velocity of the vehicle, we proceeded as follows:

- The minimum traction velocity was set to 0 kmh^{-1} (no backward motion was considered) and maximum velocity 20 kmh^{-1} .
- The EM was set to follow a straight line at constant cruise speed, for several speed values.
- Each trial was repeated 10 times for each speed.
- Data acquired during acceleration—until reaching cruise speed—or deceleration were discarded. Thus, only the instantaneous power associated with a given constant speed was registered.
- With the data acquired, a dispersion plot was obtained, and via polynomial regression, an analytical model was associated with the data. Although we tested logarithmic and exponential, among other, approaches, only the polynomial regression showed the highest R^2 .

- The analytical model obtained was then used to replace Equation (5) in Equation (13).

Figure 6 shows the dispersion plot with two polynomial regressions: second and fourth order, respectively. Since the fourth order regression showed the highest R^2 , it was the one used in this work. Higher order polynomial fitting showed no significant difference with the one chosen here.

Therefore, the velocity profiling model used in this work is the one shown in Equation (15).

$$P_{battery,k} = (-0.0007v_k^4 + 0.0305v_k^3 - 0.4383v_k^2 + 2.7563v_k) \quad (15)$$

$$with v_k = \frac{1}{\Delta t}((x_{ref,k+1} - x_k) \cos \phi_k + (y_{ref,k+1} - y_k) \sin \phi_k))$$

It should be mentioned that Equation (15) also includes the engine efficiency. The fact that it is fourth order implies that unmodeled issues were also included and were not reflected in the approximation shown in Equation (5).

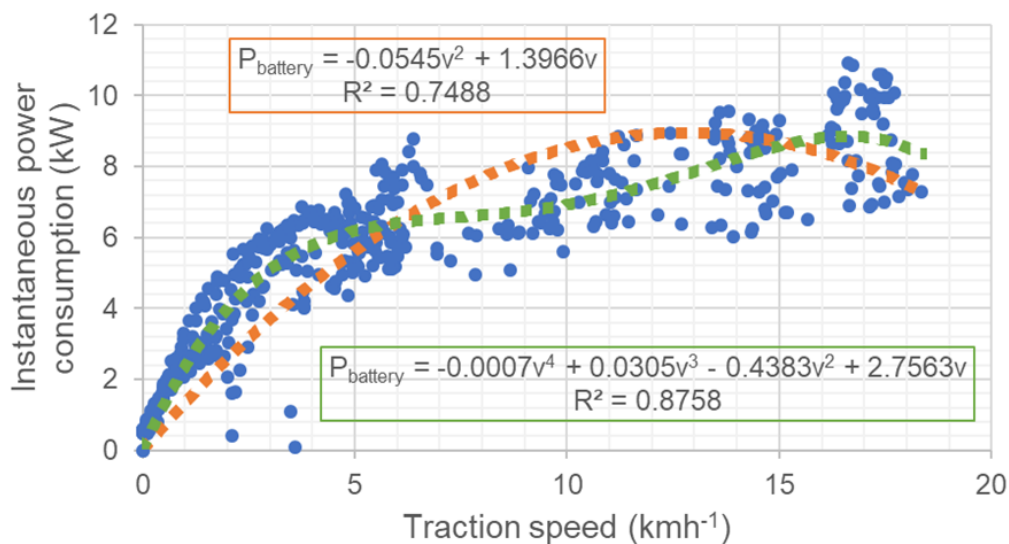


Figure 6. Model of the IPC vs. different velocities, for a second and a fourth order polynomial fitting.

3.2. RPP Results

To depict the usability of the technique presented here, below we show three examples. In Figure 7a, the distance among any two consecutive way-points was set to 0.05 m; in Figure 7b, the distance was set to 0.1 m; and finally, in Figure 7c, the distance among two consecutive way-points was set to 0.2 m. The route shown in Figure 7 is a classical solution to the RPP for traversing through corridors, published in [11] and implemented here. The trajectory tracking controller implemented to follow such a route was the one published in [21]. The starting position of the EM for the three cases was the same. At first sight, there was no difference among the paths traveled by the vehicle. However, according to the sensors and processing hardware on the EM, for traversing the route shown in Figure 7a, the EM required 4647.0 J; for the case shown in Figure 7b, 4259.3 J; and finally, 3610.7 J for the case shown in Figure 7c. As can be seen, the higher the distances among any two consecutive way-points, the smaller the energy needed to traverse. The later is due to the fact that the EM reaches the end of the path faster when the speed is high.

Nevertheless, Figure 7 shows the energy consumed by the EM after traversing the route. Using the approach shown in Section 3.1, we found that after profiling the IPC and using 0.1 s as the sampling time of the system, the energy profiled for such a route was 4.587.4 J for the case shown in Figure 7a; 4232.2 J for Figure 7b; and 3599.1 J for Figure 7c. It would seem that the energy profiling method

is accurate. However, a systematic experiment was carried out to actually test the accuracy of the method. With the same route shown in Figure 7, the distance among any two way-points varied from 0.01–0.3 m (higher distances would cause actuation saturation problems), and trials were repeated ten times per each distance. Figure 8 shows in black circles the energy consumed per each trial and in solid magenta crosses the energy profiled by our methodology.

In Figure 8, the maximum error amongst the profiled energy and the real energy consumed during the trials was ± 95 J, approximately, which is nearly 8% of the total energy required, on average. As can be seen, the profiling method is shown to be accurate according to the trials performed. In particular, differences between the profiled energy and the measured one, such as the one observed for the 0.03 m case in Figure 8, can be attributed to slippage or sinkage experienced by the EM, since it traverses at very low speeds. However, in general, the profiled energy is always smaller than the one measured, since Equation (15) does not include possible disturbances (spurious grades of the terrain, rocks and depressions, or even slippage, among others).

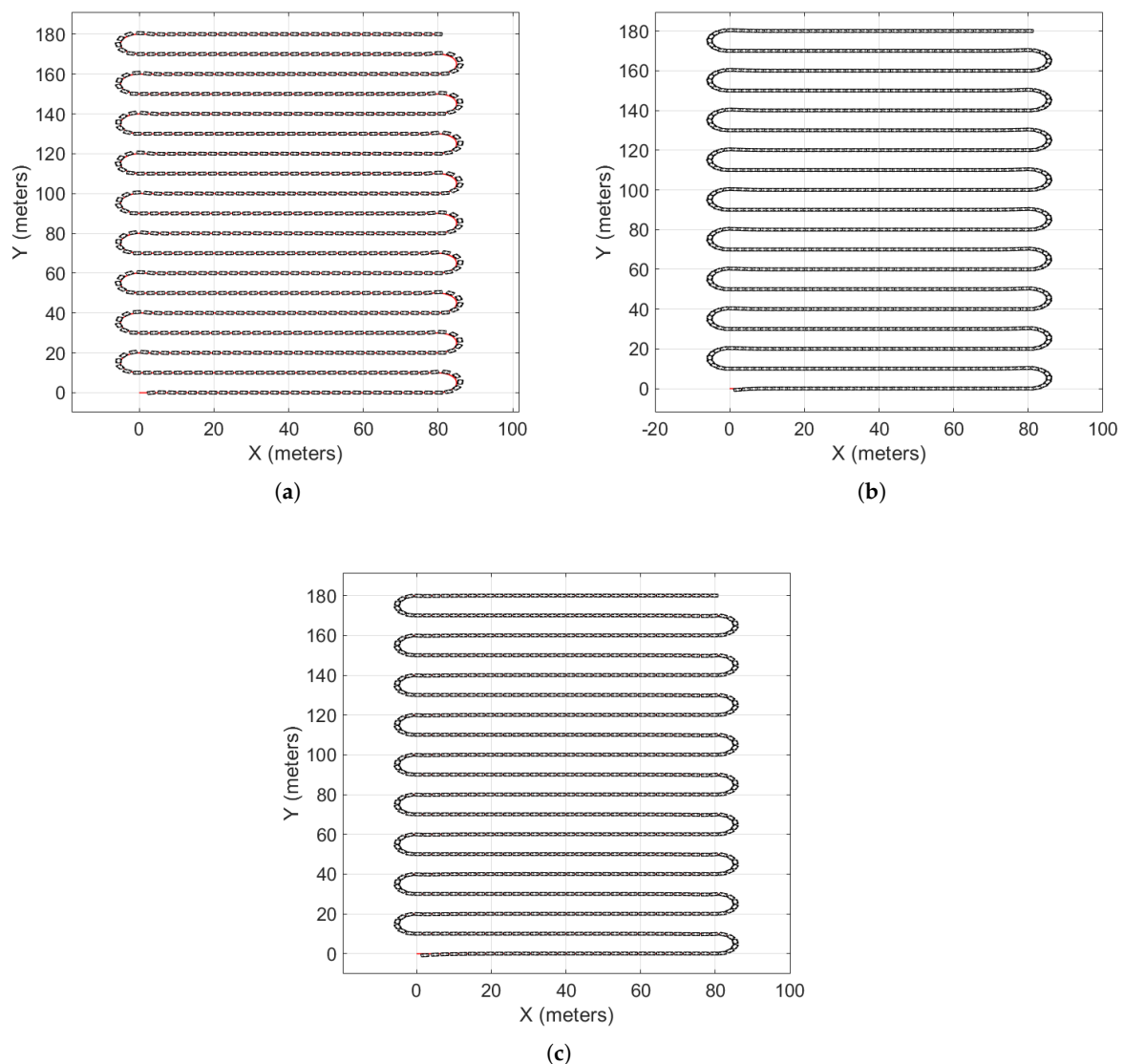


Figure 7. Three cases study. In (a), the distances among way-points is 0.05 m, and the energy required to traverse the route is 4647.0 J; in (b), the distance is 0.1 m and required 4259.3 J; whereas in (c), the distance is 0.2 m and required 3610.7 J.

The power and energy profiling capabilities of our proposed methodology were not restricted to routes with consecutive equally distanced way-points. On the contrary, the case shown in Figure 9a is a typical maneuvering case during harvesting: when traversing through corridors, the EM speed is lower than when turning (yellow shaded areas). Thus, for this case example, and considering a 0.1-m distance between consecutive way-points in the corridors and 0.15 m in the corners, the amount of energy required to perform the task was 4034 J, approximately, and 3995 J of profiled energy. A similar case is shown in Figure 9b, where we deliberately set the distance between consecutive way-points in the orange shaded area to 0.05 m. The energy consumed was 4128 J according to our sensors, and 4050 J was the energy profiled.

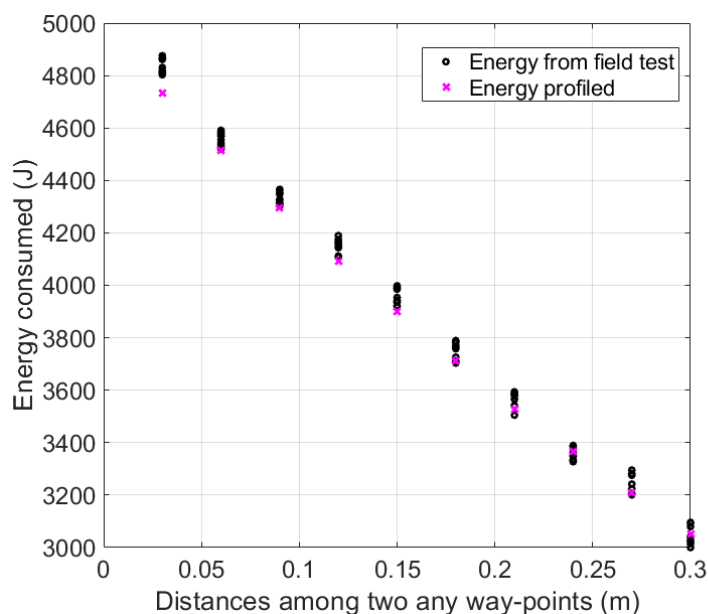


Figure 8. Energy assessment for ten trials, varying the distances between two consecutive way-points from the route shown in Figure 7. The black circles show the real energy measured from the EM sensors, whereas the magenta crosses represent the profiled energy for each trial.

Finally, with the aim of using the advantages of our methodology for profiling IPC and energy on EMs, and based on Equation (14), we performed the trial shown in Figure 10. It shows a satellite view of the experimental farm. Following the guidelines published in [11], we proposed a route to be followed by the EM, starting from and ending at the same position on the farm. The route was divided into three parts, each one with different energy constraints. The aim of the trial was to find the best Δx and Δy —see Equations (13) and (14)—given, previously, the available energy remaining in the EM. The method implemented for sorting Δx and Δy was based on a Monte Carlo approach, and it was previously published by the authors in [25]. It should be noted that for solving this problem, we did not consider time restrictions, but only energy constraints, as shown in Equation (14). For the red route, the energy constraint was set to 5000 J. Since such a constraint was given for the profiling stage, it was expected that the actual energy was higher, as was the case shown in Figures 7–9. Our methodology found that to achieve such a constraint, the distance among two consecutive way-points had to be 0.25 m; the energy profiled was 4890 J, and after the trial, the energy measured was 5050 J, approximately. For the yellow route, the energy constraint was set to 10,000 J, the distance among consecutive way-points was found to be 0.17 m, the energy profiled was 9847, and the energy consumed was 10,120 J, approximately. Finally, for the magenta route, the energy constraint was set to 100,000 J, the distance among consecutive way-points was found to be 0.12 m, the energy profiled was 98,458 J, and 101,140 J of consumed energy. As in all experiments shown in this work, the motion controller implemented on the EM was the one presented in [21].

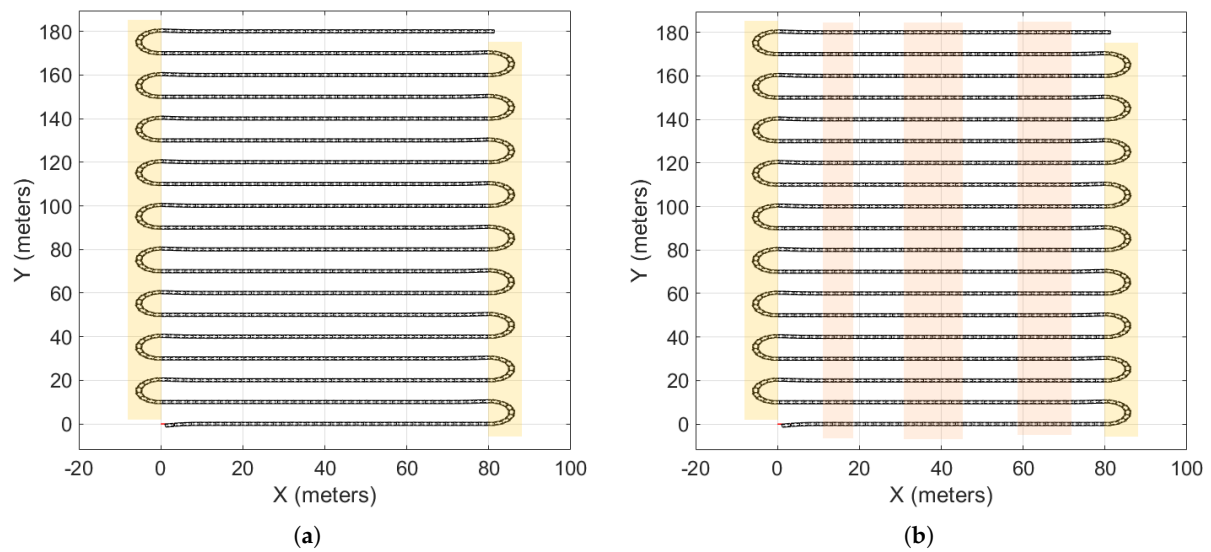


Figure 9. Examples of different power and energy profiling over the same route. Yellow and orange shaded areas represent parts of the route where the vehicle achieved different speeds, and therefore, the energy required to fulfil the route was different. In (a), during turns, the vehicle's velocity was higher than when traversing the corridors; the energy required was 4037 J, whereas that profiled was 3995 J, approximately. In (b), in the orange shaded areas, the velocity was lower than in the rest of the corridor. The energy required to fulfil the route was 4128 J, whereas that profiled was 4050 J.



Figure 10. Long-term experimentation. Yellow, red, and magenta routes have different energy constraints, which force the RPP to re-sample the distances among consecutive way-points. For the red path, the energy constraint, the energy profiled, and the energy measured were 5000 J, 4890 J, and 5050 J, respectively. For the yellow path, the energy values were 10,000 J, 9847 J, and 10,120 J (energy constraint, energy profiled, and energy measured); whereas for the red path, they were 100,000 J, 98,458 J, and 101,140 J, respectively.

4. Discussion

During the trials, a number of lessons were learned.

1. The modeling of the EM did not consider the effect of the temperature on the engine. Moreover, the efficiency of the system, η —see Section 2.3—was assumed constant. The latter is not entirely true, since the efficiency of the engine might vary according to the internal temperature, as stated in [19,22], and thus, η is actually a dynamic, and not a static, coefficient. Its modeling and how it affects the IPC will lead the future work of the authors.
2. When modeling the IPC, several assumptions were made, such as: flat terrain, negligible aerodynamic resistance, rigid wheels on the EM, and constant mass, among others. Such assumptions were necessary for the theoretical analysis, although the empirical analysis led to the fourth order model found in Section 3.1. It should be noted that the model obtained applies only for the terramechanic characteristics of the terrain where the experimentation was carried out. If the terrain changes, say to gravel, then the model from Figure 6 should be re-obtained by repeating the methodology presented in this work. However, the profiling technique shown in Section 2.5 is independent of the nature of the terrain.
3. To profile the IPC, an algebraic approach was used, which was based on the kinematic model of the vehicle (positioning only). It would be expected that if the dynamic model were used instead, then the profiling could reach better accuracy indexes than the reported ones. Including the dynamic model of the EM will also lead the future work of the authors. It should be noted though that Equation (11) assumes that the vehicle effectively reaches the desired position at the next sampling time, thus the importance of the motion controller implemented. Otherwise, positioning errors could cumulate and saturate actuators.
4. Optimizing the RPP by varying the distance among way-points as shown in Equation (14) was shown to be an encouraging approach. However, finding such distances was an off-line procedure, as the vehicle did not update the way-points as it traversed the agricultural field. It remains as an open field of study to explore what would happen if such a distance is real-time adjusted according to the energy availability of the system, since, as reported in [26], the stability of the controller could be compromised, as well as actuator saturation problems could arise.
5. The mass of the system plays a crucial role, as shown in Equation (13). It is the future work of the authors to analyze how the profiling technique can be implemented when mass changes are present in the system (such as in the case of harvesting, seeding, or herbicide spraying).
6. Although the technique shown in this work was implemented on an EM for agricultural processes, it could also be extended to other applications, such as mining, construction sites, or urban navigation.
7. A prognostic analysis of the battery remains yet to be done, which was not considered in this work, and it will also lead the future work of the authors.

5. Conclusions

Electro-mobility in agriculture is one of the challenges for the next few years. In this work, an algebraic technique was presented for profiling the instantaneous power consumption and energy of an electric machinery used for agricultural purposes. Such a profiling strategy was used for enhancing the route planning problem, since it was able to determine the velocities that the vehicle should reach to achieve the energy and power constraints imposed in the motion problem. Several trials were carried out in an experimental olive grove, showing that our proposal achieved an error smaller than 10% for estimating the IPC and the energy for all the trials, making it a reliable technique for route planning enhancement in agriculture. Hence, the presented technique could be used by the farmer for improving agriculture-related decisions.

Author Contributions: Mathematical formulation, F.A.C.; experimental set-up preparation J.E. and J.R.S.; field experiments, J.R.S.; resources F.A.C. and J.E.; data analysis, J.R.S. and F.A.C.; writing and proofreading, F.A.C. and J.R.S.; funding acquisition, F.A.C.

Funding: This research was founded by CONICYT Fondecyt grant 1171431, CONICYT FB0008 and CONICYT-PFCHA/MagísterNacional/2018 - 22170689.

Acknowledgments: The authors would like to thank to Universidad Técnica Federico Santa María and to the Advanced Center for Electrical and Electronic Engineering (www.ac3e.cl).

Conflicts of Interest: The authors declare no conflict of interest.

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