# Automation and Optimization of Working Speed and Depth in Agricultural Soil Tillage with a Model Predictive Control based on Machine Learning

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## Abstract

While facing environmental challenges due to climate change, the need for optimization and automation of agricultural tasks is increasing. Furthermore, costs and the lack of qualified personnel require efficient and highly automated control systems for agricultural machinery. Therefore, this work addresses these challenges by optimizing the working speed of a tractor and soil tillage implement combination to maintain efficient operating points during high power demands.

A system was developed that predicts a suitable working speed based on a draft force and traction model in combination with the usage of a neural network for fuel rate prediction. The machine operator is able to customize optimization parameters such as fuel efficiency, performance or total costs depending on the individual needs and situation. These parameters lead to a reward function to value the machines state. Based on these objectives the network is able to predict the system state for various potential target speeds and evaluate their optimization parameters to select the most promising target speed. This target speed gets received by the tractor and leads to a new machine state.

The fuel rate prediction network is trained on previously collected training data. Using different methods, for example transfer learning, the network can be adapted easily to different sizes and types of tractors. As the draft force models are based on equations, they can be changed to adapt to turning and no-turning soil tillage.

To maintain a sufficient working quality and simplify online parametrization of draft force requirements, the implement working depth is automatically adjusted based on active Lidar

measurements. The adjustments take the working conditions and agricultural requirements into account.

The system was validated during field measurements on different locations with various customized optimization parameters. The results show a suitable reaction to changing operating conditions.

## Introduction

The need for process optimization and automation in agricultural tasks increases due to environmental challenges and cost pressure. To handle these complex and multidimensional tasks, advanced control architectures are required. The deployment of artificial neural networks allows the development of advanced control systems without the previously necessary modeling work. However, obtaining insights in the specific decision making of such systems is difficult and limits the usability due to safety concerns.

This paper presents a method based on traditional traction and draft force modeling combined with an artificial neural network for fuel rate predictions to combine the positive aspects of both approaches.

Furthermore, the functioning of the system is evaluated during experiments in field tests.

## Related Work

Kautzmann and Geimer developed an approach for holistic efficiency optimization in agricultural processes. Their approach is based on an System under Observation and Control (SuOC) algorithm, observing the current state of the vehicle and suggesting new state transitions based on an evolutionary algorithm. [1; 2]

Becker et al. proposed a Reinforcement Learning Approach for speed optimization during the ploughing process. Hereby an agent is trained in optimizing different reward functions such as the fuel efficiency. [3] Schreiber developed a modeling approach for fuel optimization that requires precise knowledge on the functioning of the machine but is able to compute the energy requirements in different agricultural processes. [4]

Li et al. draft force model based on ASAE D497 and measured real-time data to optimize and automate the gear shifting process in agricultural tasks. [5]

## Working Depth Control

During measurement data collection a wide variation in working depths was detected even though the rear linkage position remained static during data collection. This occurred due to the change in draft force requirements during soil composition changes.

There are systems available that change the position of the implement dependent on draft measurements or slippage measurements, but to guarantee a constant working depth, additional measurements must be taken. To guarantee an adequate cultivation quality and to counteract depth changes during speed adaptations, an automated working depth control system was used based on lidar measurements. The lidar sensor thereby creates a point cloud of the surface structure which is used to calculate the surface plane with the RANSAC algorithm. [6]

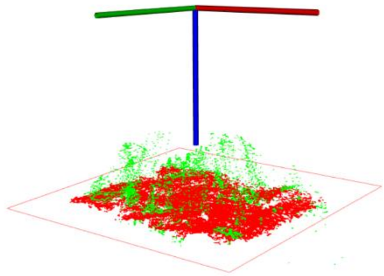

Fig. 1: Plane Detection

A PID-controller uses the measured depth and regulates the lift arms to keep the working depth at a specified level.

## System Modeling and Control Strategy

The model requires access to internal machine measurement data such as theoretical speed ($v_{theo}$) which is calculated from engine revolutions and gear ratio, the real speed ($v_{gnss}$) which is derived from GNSS-measurements, and the pitch angle ($\theta$) which is used together with a static offset in order to approximate the slope angle ($\delta$). The slippage ($\sigma$) can then be calculated using the speed measurements.

Furthermore, the model requires either draft force ($F_D$) or traction force ($F_T$) measurements. The first can be measured using force sensors at the lower links to the implement, the latter can be calculated from gear box pressures if the tractor features a hydraulic continuous various transmission. One of both values is sufficient, since both values are dependent on each other which is described in the following.

There is a wide variety of models that describe soil-tire interactions. [7] The traction model developed by Schreiber and Kutzbach, which was improved by Meiners; Böttinger and Regazzi is one of the most commonly used ones. [8; 9] However, this model as well as other models focus on accurately describing these interactions rather than being easily adaptable for online parameterization.

Therefore our model uses the traction model described by Jacke and Drewes, which was developed for forestry machines. [10]

This allows an online parametrization with minor simplifications, because the model features less degrees of freedom.

$$F_T(\sigma) = a_T + b_T \cdot \sigma + c_T \cdot \sigma^2$$

Based on the shape of usual traction-slippage curves, the following simplifications are used in order to reduce the degrees of freedom for online parameterization.

$$\kappa(\sigma = 0) \approx 0$$

$$\dot{\kappa}(\sigma = 0.6) \approx 0$$

This eliminates the variables $a_T$ and $b_T$.

$$F_T(\sigma) = 1.2 \cdot c_T \cdot \sigma - c_T \cdot \sigma^2$$

Online-parametrizable models for draft force relationships already exist. Harrigan and Rotz developed the draft force model which is used in this work. [11] The model includes machine-specific parameters ($a_D, b_D, c_D$), the width of the implement ($w$), the working depth ($t$), and a soil specific parameter ($s_D$). Their findings were later captured in the ASAE D497.4 standard. [12]

Rößler; Kautzmann and Geimer proposed the usability of an adaption of the formula for online parametrization. [13]

However, this work uses the original formula to avoid the necessary simplification.

$$F_D = s_D \cdot \left(a_D + b_D \cdot v_{gnss} + c_D \cdot v_{gnss}^2\right) \cdot w \cdot t$$

The implement-specific parameters are derived by the conclusion of extensive experiments by Harrigan and Rotz, who elaborated these parameters for a wide variety of implements. [11] Because the working width is constant, it is possible to parametrize the only remaining soil specific parameter based on online measurements of the speed and draft force of the tractor. Since the horizontal weight force $F_{W,h}$ can also be calculated using measurements of the slope angle and the previously measured weight of the machine combination, traction and draft relationships are combined.

$$F_T = F_D + F_{W,h} + F_R + F_{air} + F_{acc}$$

Air resistance $F_{air}$ as well as accelerating force $F_{acc}$ are neglected due to the constant operating conditions and low working speeds. Rolling resistance $F_R$ can be considered with a static friction coefficient $\mu$.

This results in a single formula that only leaves unknown variables: theoretical and real speed of the vehicle.

$$1.2 \cdot c_T \cdot \left(\frac{v_{theo} - v_{gnss}}{v_{theo}}\right) - c_T \cdot \left(\frac{v_{theo} - v_{gnss}}{v_{theo}}\right)^2 = s_D \cdot \left(a_D + b_D \cdot v_{gnss} + c_D \cdot v_{gnss}^2\right) \cdot w \cdot t + F_{W,h} + \mu \cdot F_{W,v}$$

On this basis, traction and draft forces can be elaborated for different hypothetical working speeds ($v_{theo}$) and the obtained relationships are the input variables for the neural network that is used for fuel rate prediction. The calculation of these variables is illustrated in Figure 2.

The artificial neural network described in Figure 3 uses the complete input parameter set to predict the fuel rate ($B^{\sim}$). This network is trained on previously collected measurement data and does not require online learning.

A total of 72,493 full parameter sets from approximately 5 hours of recorded cultivation time were used to train the artificial neural network. These data sets were filtered to clear turning maneuvers as well as to smooth out sensor fluctuations using a moving average filter. After the filtering process 53,773 parameters remained.

The network structure is optimized using a Hyperparameter Search based on the Hyperband algorithm resulting in the final structure of nine densely connected hidden layers each containing 256 neurons with a ReLu-Activation function. [14]

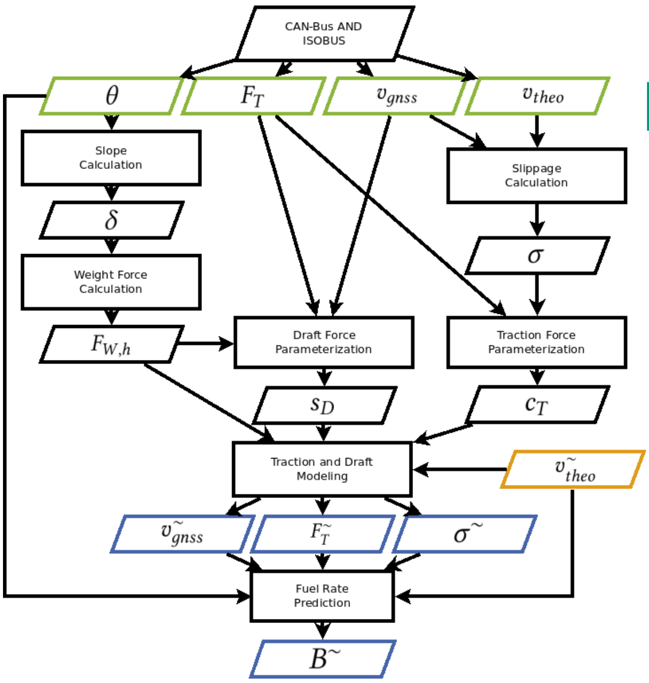


Fig. 2: Dataset Generation

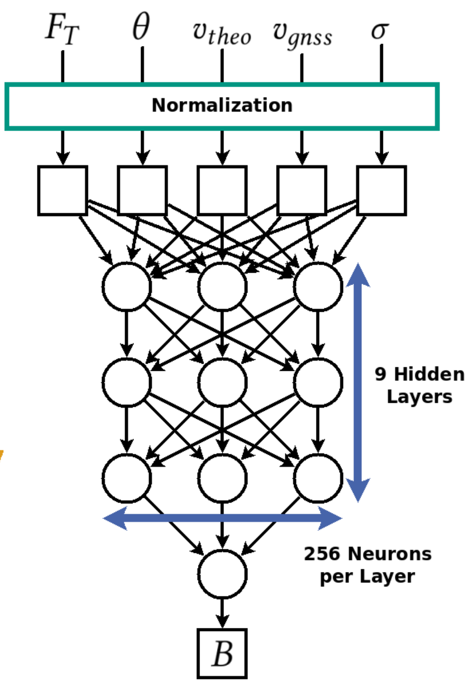


Fig. 3: Neural Network Structure

This network then computes the fuel rate ($B^{\sim}$) for the specified parameter set and thereby allows a comparison between the different sets.

This comparison is conducted using different reward functions ($R$) such as to optimize fuel efficiency $R_{efficent}$

$$R_{efficient} = \frac{v_{gnss} \cdot w}{B}$$

or to maximize the working speed with the reward function $R_{performant}$

$$R_{performant} = v_{gnss} \cdot w$$

Other options include the minimization of the total working cost.

After comparing the different generated parameter sets, the one with the highest reward is chosen and set as an updated target speed since the continuous various transmission of the tractor does not require choosing gears.

These optimization cycles run approximately one time per second, allowing for a fast adaptation to changing ambient or soil conditions. Only the current speed and a 0.5 km/h slower as well as a 0.5 km/h faster speed setting were elaborated in order to reduce computational effort.

## Evaluation

Fig. 4: System Testing

To validate and test the developed system, a Fendt 516 Vario tractor was used together with a Horsch Terrano 4 FX cultivator as implement. The test machine was equipped with an ubuntu based computer with CAN-Bus interfaces to run a ROS node receiving sensor signals from the tractor an sending parameters back. Furthermore this computer is connected to a local LAN network to receive additional sensor data, for example lidar scans for working depth estimation, as explained before.

To perform the test runs on the field, tractor and cultivator were adjusted manually to work within the desired ranges of working speed and working depth. This applies to the top link position, levelling discs and packer roller. After these set up, parallel rows were driven on the same field for evaluation. Every row begins with an ascent to the hill top in the center of the field, followed by a descent to the end of the field. The first row was driven by a human driver as reference measurement, which is represented by the green line in Figure 5 and 6. The orange and blue line belong to the rows driven with activated control system. As demonstrated in the graphs, the control system was able to perform soil tillage with both reward functions.

The evaluation in the following section will start at a driven distance of 30 m in each row to allow every algorithm to settle at a stable point.

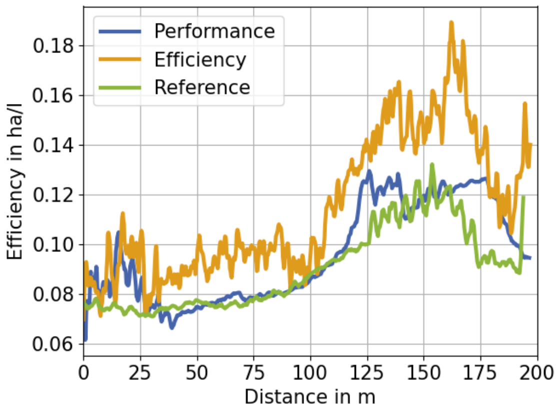


Fig. 5: Efficiency Results

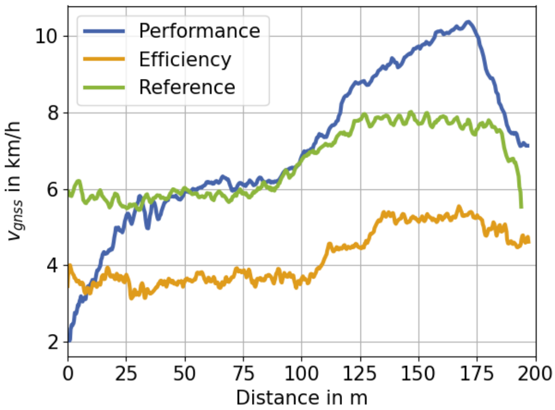


Fig. 6: Performance Results

With a closer look, both reward functions and the reference show a similar efficiency for the first half of the field. This can be explained by similar working speeds and therefore similar motor loads. After reaching the top position of the field, the performance reward function keeps accelerating the tractor, while the reference driver stays with 8 km/h. The efficient reward determines lower velocities to be the most efficient working speed and stays at 4 km/h in the uphill section and about 5 km/h within the downhill section.

Compared to the reference, the control system with activated efficient reward function was able to reduce the fuel consumption by 19 %, whereby it has to be noted that the working depth variations for the human reference driver could have influenced these results. Comparing reference and performance reward function, an increase of the mean velocity of 9 % can be achieved.

Table 1 shows a summary of all results.

| | **Mean Velocity in km/h** | **Mean Fuel Rate in l/ha** |
|---|---|---|
| **Reference** | 6.74 | 11.30 |
| **Efficient** | 4.20 | 9.16 |
| **Performant** | 7.32 | 11.10 |

Table 1: Evaluation Results

## Conclusion

The proposed system presents a new method for speed control automation during agricultural tillage processes. Traditional system modeling techniques are used to describe the vehicles state and a neural network predicts the fuel rate in each state. With this combination, operating security and easy adaption to other processes can be combined.

In conclusion, the system was able to improve the cultivation process depending on the targets of the driver while maintaining an adequate tillage quality.

The results show that the method can be used to reduce fuel consumption as an economic advantage as well as to reduce exhaust emissions to protect the environment.

In the future, the option to improve the equations used for traction and draft modeling should be elaborated to optimize the method.

The speed control system can also be combined with a flexible implement position control to lift the implement during difficult operating procedures. This prevents the vehicle from getting stuck due to excessive traction force requirements which cannot be supplied with low traction coefficients. Additionally, the system can be extended with process sensor systems to monitor and optimize the process quality. Without such additional features, a human driver is still necessary.

Furthermore, there are already experiments to transfer the trained fuel rate prediction model on other tractors with different engines and transmissions while minimizing the effort of new training data collection. If successful, this method would reduce the necessity of cost-intensive measurement data collection.

Further research is required to extend the choice of working speed to an additional gear shift parameter to allow adaptation on vehicles without a continuous various transmission.

# Literature


[1] Kautzmann, T. et al.: Holistic Optimization of Tractor Management – Organic Computing in Off-highway Machines. LAND.TECHNIK AgEng (2011), S. 275-280.

[2] Kautzmann, T. und Geimer, M.: A novel approach for holistic optimization of mobile machine managements. Proceedings of the 12th Scandinavian International Conference on Fluid Power (SICFP'11), Tampere, Finland, May 18-20 (2011), S. 15.

[3] Becker, S. et al.: Machine Learning for Process Automation of Mobile Machines in Field Applications. LAND.TECHNIK (2019), S. 187-197.

[4] Schreiber, M.: Kraftstoffverbrauch beim Einsatz von Ackerschleppern im besonderen Hinblick auf die CO2-Emissionen. (2012).

[5] Li, B. et al.: Automatic gear-shifting strategy for fuel saving by tractors based on real-time identification of draught force characteristics. Biosystems Engineering 193 (2020), S. 46-61.

[6] Fischler, M. A. und Bolles, R. C.: Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. Communications of the ACM 24 (1981) H. 6, S. 381-395.

[7] Geimer, M.: Mobile working machines. Warrendale, Pennsylvania (USA): SAE International 2020, DOI: 10.4271/9780768094329.

[8] Schreiber, M. und Kutzbach, H.: Influence of soil and tire parameters on traction. Research in Agricultural Engineering 54 (2008).

[9] Meiners, A.; Böttinger, S. und Regazzi, N.: Triebkraft/Schlupf-Verhalten von Ackerschlepperreifen – praxisnahe Messung und Simulation mit dem Hohenheimer Maschinenmodell. LANDTECHNIK (2020), Bd-75 Nr. 1.

[10] Jacke, H. und Drewes, D.: Kräfte, Schlupf und Neigungen - ein Beitrag zur Terramechanik forstlicher Arbeitsmaschinen. Forst und Holz (2004).

[11] Harrigan, T. und Rotz, C. A.: Draft Relationships for Tillage and Seeding Equipment. Applied engineering in agriculture 11 (1995), S. 773-783.

[12] N.N.: ASAE D497.4 Agricultural Machinery Management Data. (2003), S. 9.

[13] Rößler, P.; Kautzmann, T. und Geimer, M.: Online parametrierbare Traktor-Gerätemodelle. LANDTECHNIK 67 (2012) H. 4, 247-250.

[14] Li, L. et al.: Hyperband: A Novel Bandit-Based Approach to Hyperparameter Optimization. Journal of Machine Learning Research 18 (2018) H. 185, S. 1-52.