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Predictive operation strategies for future machine concepts

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Improving the efficiency and performance of agricultural machinery calls for innovative control approaches. When these approaches are applied at superordinate control unit level to optimize operation behavior, we speak of operation strategies. This paper examines an approach for structuring an operation strategy that is capable of using predicted cycle information. This predictive character makes it possible to use optimization processes as a way of achieving better efficiency and/or performance. A tractor is used as an example application. On account of its many different work tasks, this demands a highly flexible control approach. The following article illustrates how this can be shaped, how the necessary sub-elements are configured and which results can be expected from applying the operation strategy presented.

Keywords
Operation strategy, prediction, dynamic programming

The powertrain in mobile work machines consists of many different components. In a tractor, the main components are the combustion engine, the transmission and the hydraulics. An operation strategy must ensure that the various components of the powertrain operate in a coordinated and well-balanced manner. Using a quality criterion (e. g. fuel consumption, maximum area coverage etc.), the optimization objective can be set for the operation strategy. Operation strategies can be subdivided into the three configuration levels of

- control-based,
- online optimum and
- predictive strategies.

Complexity and the development and research input increase as we move towards the predictive operation strategy. Compared with the other types, predictive operation strategies provide the capability of setting the machine parameters to the future machine state at the best possible time, e. g. increasing the degree of engine utilization in response to a predicted fall in load by adjusting the transmission ratio. This not only makes it possible to respond to current operation conditions but also to act in a predictive way. Furthermore it permits optimization of transient machine states or highly dynamic load cycles, e. g. Y-cycle for front-loader activities. Prediction has the task of determining the future load requests given to the machine's powertrain. Generally speaking, a distinction can be drawn here between the use of internal and external machine data. External data, for example, can be soil maps, weather information or logistical data. The approach in hand focuses exclusively on the use of internal machine data. This means it is possible to use all measurable machine information – in this case, powertrain information in particular. By recognizing the pattern of machine operation states and after the system has completed a learning phase, the subsequent operation states can be predicted with defined probability on the basis of the preceding operation states. Consequently, the

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approach presented here differs from model predictive approaches. Model-based optimization of the machine only takes place in the system's optimization element which contains the machine's actual operation strategy.

In the passenger car segment, prediction is used, for example, to optimize the flow of energy and increase driver safety. For instance, a predictive battery and powertrain management system is used by Back (2005) to match the battery's state of charge and other powertrain parameters to the predicted journey. Gosslau (2009) has developed an approach for controlling the cooling system on a predictive basis. Here, cooling system control is influenced by journey-type and journey-profile recognition information as well as by determining the type of driver, making it possible to increase the temperatures in the system by reducing the safety margin to the maximum permissible temperatures. This results in lower fuel consumption. Kretschmer et al. (2006) use vehicle speeds and distances between vehicles to recognize a passing maneuver and predict its duration as a means of increasing driving safety while passing another vehicle.

Predictive control approaches, e. g. in the form of predictive cruise control, are nowadays state of the art in commercial vehicles. In addition to the data on the vehicle's state, they use external information, such as the altitude profile and recommended maximum speed for the route traveled as the basis for predicting the anticipated load cases and determining the most efficient speed and acceleration profile (Terwen 2009, Kern 2013).

Using predictive strategies in mobile work machines, and especially in the tractor, is far more ambitious. The particular challenge lies in incorporating many different work processes with associated disturbance variables and the resultant, fluctuating process parameters, variable ambient conditions and operator influences. Operation strategies currently used in tractors are usually control-based strategies to control the drivetrain parameter.

Model-based control approaches are found in the field of controlling the work processes of mobile work machines. For example, Happich (2012) has examined a model-based loading control system for transferring chopped material in parallel operation. This approach involves a model for configuring the material cone on the transport unit in relation to throughput, this being taken as the basis for adjusting the impact point of the jet of chopped material in such a way that the transport unit can be filled evenly and automatically. Predictive elements are used, for example in the "marion" project (Reineke et al. 2007) as part of planning systems. One example application in this project is the planning of harvester paths and the planning of transfer points in grain harvesting with the aim of automating the combine harvester/transfer vehicle combination on the field.

The motivation for developing and applying the approach presented below lies in using it as a development tool for developing machines as well as in using it in machine deployment practice. The aim is to extend the operation strategy to cover all of the machine's power users and optimize the way in which the machine's potentials are exploited. Reference is made to Töpfer et al. (2014) as the basis for this paper.

Requisite system components

The approach proposed here with a tractor as the application example comprises the three main components work task classification, prediction and optimized operation strategy (Figure 1).

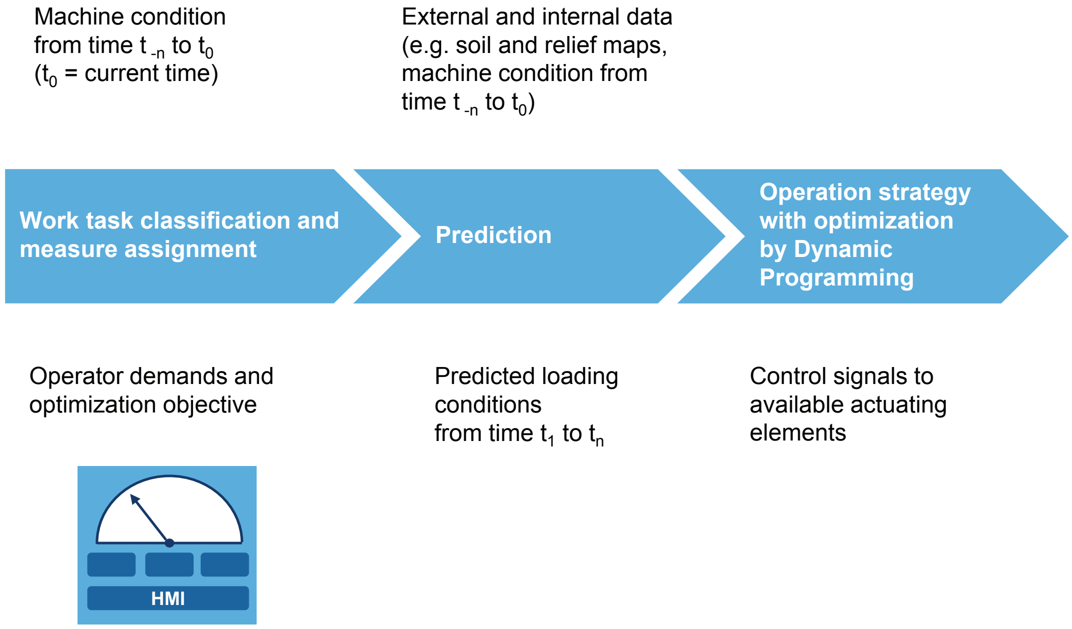

Figure 1: Potential system structure

Work task classification and measure assignment

The first block, classification of the work task, is needed to ensure that the operation strategy only uses measures that make sense under the aspects of optimization and are compatible with the machine's current work task. The quality of the work result must not be negatively influenced. For example, engine speed must only be reduced if the actual speed of a process-relevant work drive unit can be kept more or less in the region of the target speed. This makes it necessary to classify machine states first. Here, it is less important for the work task to be identified in any distinct and precise way. Instead, it is necessary to identify in a learning phase the requirements placed by the current work task on the machine and the resulting machine states. Against this backdrop, it seems expedient to define four requirement classes:

- Constant quasi-steady-state cycle (e.g. soil tillage)
- Dynamic, periodically recurring cycle (e.g. Y-cycle)
- Dynamic, non-periodically recurring cycle (e.g. transport activities)
- Work process without or only with intermittent use of propulsion

Each class is assigned a package of measures which can be used by the operation strategy. Individual package measures can also be excluded by analyzing the operation pattern and operator input.

As applicable measures, it is possible in principle to exploit all control capabilities and the variability of power users present in the overall system. Besides obvious measures, such as optimizing engine/transmission management, many other measures are also conceivable (e.g. predictive thermal or generator management). Depending on the measures selected – of which some can be used without any modifications on the hardware side – applying them influences efficiency, dynamics and functionality.

Prediction

The second block in the system's structure involves predicting future operation states. The information used for this can be divided up into external and internal machine data. External data, such as map material providing information on soil type and relief profile as well as load states of preceding parallel travel paths, can be used for predicting operation states. Predicting operation states in work tasks without external machine data, such as GPS data, involves a more complex type of prediction which evaluates available internal sensor data and uses pattern recognition to permit a prediction of future operation states (OS) in the time interval from t_1 to t_n. To realize this prediction, it is necessary that cyclical work tasks can be broken down into a finite number of recurring operation states, with each work task comprising a specific sequence of operation states. Under this prerequisite, it is theoretically possible to apply probabilistic methods to predict which operation state sequence is most likely to follow next on the basis of the present and past operation states. Appropriate methods include hidden Markov models (HMM) and recurrent neural networks (RNN). Compared to RNN, the HMM has advantages in relation to sequence length and the stability of prediction as well as the way in which discrete states are handled.

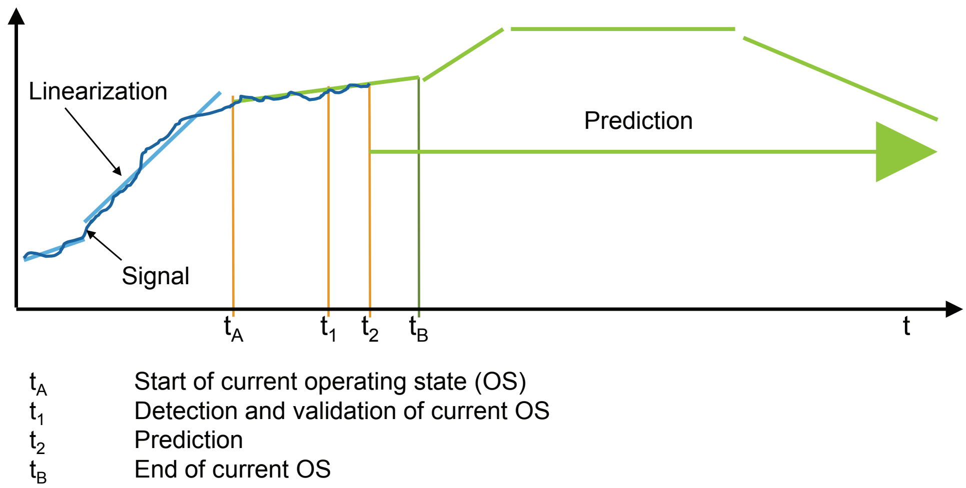

Figure 2: Recognizing and predicting operation states

The HMM is parameterized in several stages. This involves a learning phase in which the sensor data are initially recorded, prepared and linearized over time (Krogerus et al. 2013). The characteristics derived from linearization are assigned to operation states (OS). By way of example, Figure 2 shows sensor signals that have been linearized and assigned to operation states (recognized OS). The sequence of operation states is referred to as the observation sequence. The observation sequence is passed on to the HMM from which it is parameterized. With the machine running in similar recurring operation states, the aim now is to apply this procedure and, on the basis of the operation states determined from the learning phase and the parameterized HMM, assign to the current operation state (current OS) a previously defined operation state. Together with the previous operation state, this is passed on to the HMM from which it determines the operation states likely to follow (predicted OS) and therefore the loads that are likely to be requested from the machine. The prediction quality of the HMM is evaluated by comparing the predicted operation states (predicted OS) with the recognized operation states (recognized OS). In the event of any discrepancies resulting from unknown operation states, the HMM is re-parameterized. For recurring operation states (e.g. Y-cycle), the prediction can be implemented and applied in the field of mobile work machines with their many different work tasks. A significant amount of research must still be done for other irregular load cycles.

Operation strategy and dynamic programming

The third element in the proposed system structure covers the actual operation strategy using the measures available. Within this approach, dynamic programming is used for determining the optimum machine control signals with respect to the optimization objectives (quality functionals) and the constraints of state and manipulated variables (Back 2005). One optimization objective frequently used is the fuel consumption for the cycle under consideration. Other optimization objectives, such as adjusting machine parameters to suit the current and future power demands, can also be achieved with this approach. According to Guzzella and Sciarretta (2007), dynamic programming mainly differs from the optimized control approaches usually encountered in control technology by also being able to take account of complex constraints of state and manipulated variable. Dynamic programming furthermore finds the global optimum in relation to the defined optimization problem. The gradient-based optimization techniques frequently used cannot provide any guarantee of finding the global optimum. These qualities are crucial to using dynamic programming in the approach presented here.

Figure 3 shows the flow diagram for carrying out deterministic dynamic programming with the requisite inputs. This optimization method can be used in model-based machine development for calibrating control parameters as well as online while the machine is operating to determine the optimum operation parameters. In this case, the prediction results can be used as optimization input variables in order to adjust the machine to future load requests. It is also expected that this will make the approach suitable for optimizing transient machine states in dynamic cycles.

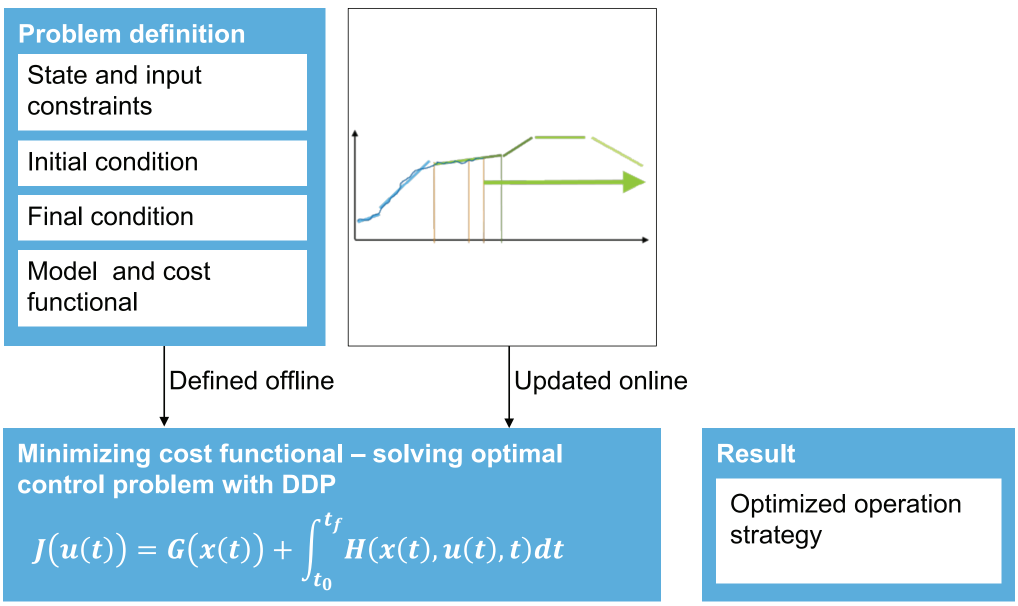

Figure 3: Flow diagram – deterministic dynamic programming

Concept Validation

The approach presented for a predictive operation strategy was developed on a model basis and tested with the aid of a validated overall machine model. By way of example, the results shown below present an excerpt of application areas for the predictive operation strategy. The theoretic field of application is very wide and primarily determined by the degrees of freedom of the powertrain components installed.

In all three examples, the quality functional is fuel consumption. Using machine power output as a quality functional must be regarded as critical in simulation. This approach usually results in a significant change in wheel/soil contact and thus in slip values. Generating an accurate simulation of these relationships is highly complex with today's state of the art. For this reason, slip conditions are kept as constant as possible in comparing the various control approaches.

Figure 4 presents an example cycle section. In comparison to a simple shifting strategy (manual shifting), which shifts exclusively in relation to engine speed, and an intelligent gearshift logic (transmission control unit), the results show the changed shifting behavior in an acceleration cycle. The changed shifting points make the engine more efficient. This significantly reduces fuel consumption.

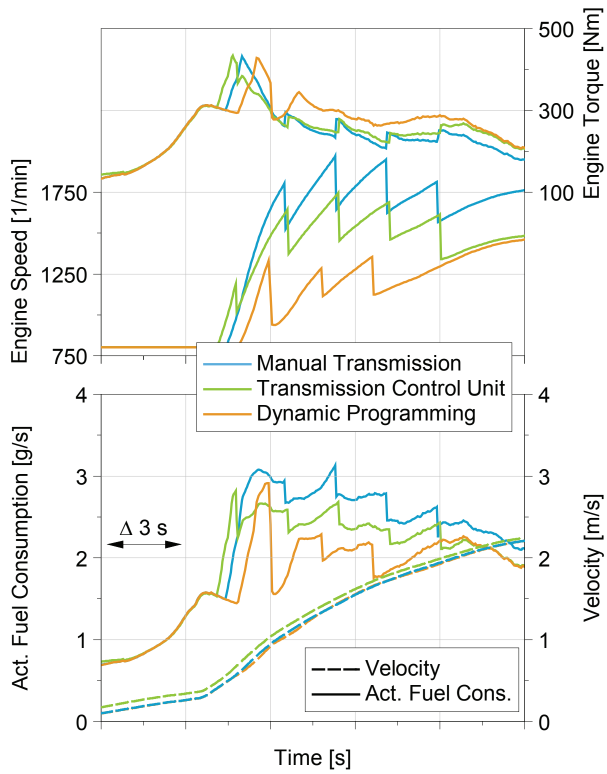

Figure 4: Results of simulating acceleration in a Y-cycle

The second example, presented in Figure 5, also uses deterministic dynamic programming to define shifting points. In this case, it not only adjusts the transmission ratio but also the power takeoff ratio. This measure assumes that the tractor has a power-shifting PTO transmission. If prediction forecasts a phase with a reduced load request (approx. second 22, Figure 5), the operation strategy optimizes the ratio of the drive transmission at the appropriate moment in order to operate the combustion engine in a more efficient map range. The PTO shaft ratio must be adjusted to keep PTO shaft speed constant as combustion engine speed varies. This ensures the operation strategy. The actual challenge in this example is selecting the time at which the transmission ratios are returned to the initial state. This must take place before the load requests from the work cycle go up again into full-load range (e. g. 90 %). Shifting down too late would lower combustion engine speed and, as a result, reduce working speed. Prediction forecasts the load curve, giving the operation strategy the opportunity to initiate downshifting at an appropriate moment (approx. second 35, Figure 5).

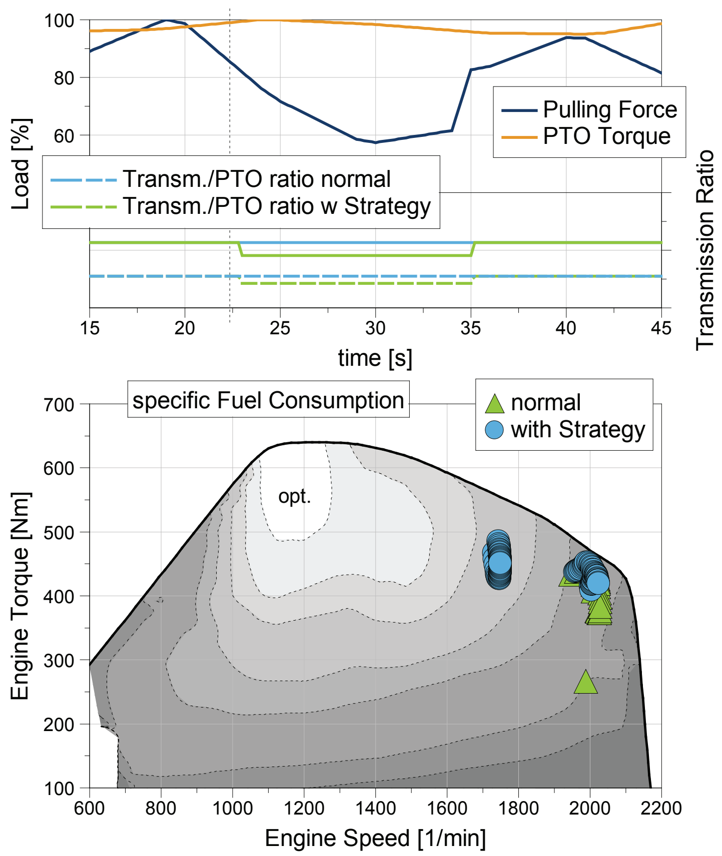

Figure 5: Varying PTO shaft ratio

The third example application in Figure 6 uses the thermal balance and the thermal masses in the cooling system to store cooling energy during headland travel. If the tractor drives into the headland after heavy pulling work, the necessary tractive work is suddenly reduced by lifting the attachment. This is also accompanied by a reduction in the cooling requirement for the combustion engine and neighboring components. In this example, the operation strategy is capable of reducing the cooling water's setpoint temperature. This increases fan output which, in turn, moves the combustion engine to a more efficient operation point. This means that specific fuel consumption falls during headland travel. Machine power output must be increased again when the attachment returns to service. As soon as it makes sense from an energy point of view, the operation strategy returns the coolant setpoint temperature to its original level. The stored cooling energy that can now be used and the associated reduction in fan output give the tractor the power reserves needed for pulling work.

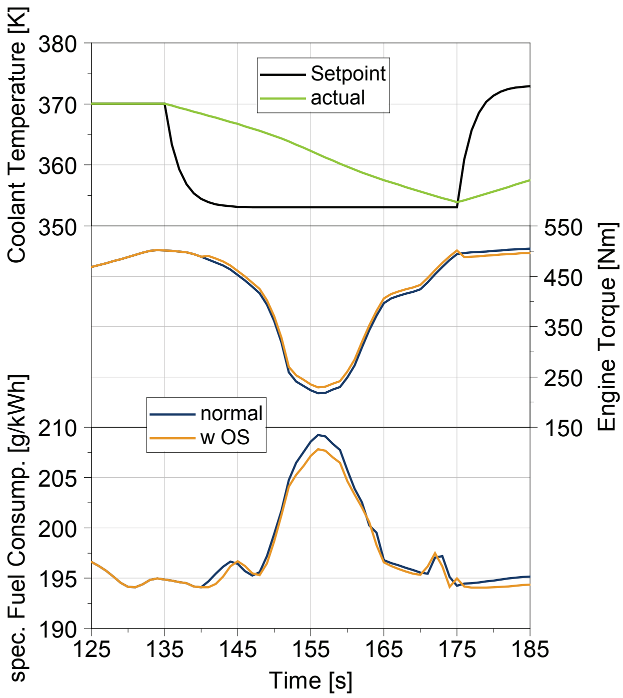

Figure 6: Headland cooling measure

Conclusions

The approach presented shows a way that is suitable for implementing a predictive operation strategy on a future mobile work machine. At the same time, elements of this approach can be applied even today in model-based machine development and in evaluating and parameterizing control-based operation strategies. One advantage of this approach lies in the fact that optimization takes account of the overall system and measures can be used which could probably not be implemented without prediction. The example results presented demonstrate realistic ways of applying the methodology in order, for example, to utilize existing efficiency-boosting potentials. Here, the potential saving is highly dependent on the application case. It is not possible to make any general statement in this regard. The next steps on the way to realizing the presented approach will involve implementing the HMM, validating the methodology and developing a virtual terminal on which the self-optimizing operation strategy will be implemented. This terminal will also form the interface to the operator.

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