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Improving Operator Skills with Productivity Model Feedback ⋆

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Abstract: The performance of a mobile working machine is subject to operating conditions, operator's actions, and technical condition of the machine. The ability of the operator has proven to be a significant factor when considering productivity or fuel efficiency. If the machine is in good technical condition with controller parameters tuned properly, the only way to increase performance, that is, productivity and fuel efficiency, is to improve the operator's skills.
The goal of this paper is to research the operator evaluation problem in the case of forest harvesters. The productivity variations of the machine between work shifts are modeled using variables that describe operating conditions and the performance of the operator in different work tasks. An adaptive-network-based fuzzy inference system (ANFIS) is proposed to model the productivity. The model is trained and validated using data from several operators measured in normal work environment during several months. An algorithm based on the gradient descent rule is proposed to give feedback about the most significant areas of improvement potential. The use of the gradient-based technique in offline analysis of the operator's performance and work style is described. The variation of the performance between the operators is analyzed and the results are discussed.

Keywords: Human factors; Productivity; Fuzzy modelling; Skill-based systems.

1. INTRODUCTION

The rapid development of sensor technology, communication networks, processing units, and data mining methods during the last decades has enabled the utilization of advanced methods in performance evaluation of industrial processes. There are countless succesful examples of utilizing fault detection and diagnosis, as well as performance monitoring methods by using only the readily available measurement data. (Chiang et al. [2001]) However, beyond mere technical performance, there exists also the possibility to consider human factors. That is, in most industrial processes where the human operator plays a key role in controlling the process, it is possible to evaluate the operator's actions. Furthermore, if the operator's actions can be succesfully evaluated, it is possible to suggest actions in order to enhance the operator's skills.

In mechanized timber harvesting, the variance of performance between operators has been studied in several spesifically arranged field tests. There are research results reporting that there was over 40 % difference between the most and least productive operator working with similar machines and in similar operating conditions. In addition to the productivity, the quality of the work has been reported to vary between operators. (Sirén [1998], Ryynänen and Rönkkö [2001] cited in Väätäinen et al. [2005]) Based on these results it is obvious that in order to utilize the whole capability of forestry machines one needs to consider to optimize not only the technical performance, but also the skills of the operators.

The productivity of forest harvesters has been researched by Väätäinen et al. [2005] in specifically organized field tests with manual recording of the operators' working styles. However, there are no reported attempts to model productivity using the measurements available during normal work. Therefore, this research is focused on modeling the productivity of forest harvesters using the measurements readily available in the database recorded during normal work. An adaptive-network-based fuzzy inference system (ANFIS) is utilized to model the productivity variations based on operating conditions and performance

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metrics recorded during normal work. The model is trained and validated by data gathered from several machines and several operators. Based on the productivity model, a gradient-based feedback algorithm is proposed to provide educative feedback about the operator's actions. Thus the performance of the machine and skills of the operator could be increased by recognizing the non-value-adding actions and by giving feedback to the operator how to avoid them.

Operator supporting feedback systems are often referred as intellingent tutoring systems (ITS). There are successful examples of utilizing ITS in various applications, like web-based training of different school subjects such as physics or mathematics reported by Ozdemir and Alpaslan [2000], or operation of an industrial process reported by Hiroshi et al. [1996]. Nevertheless, the developed systems are usually based on training students by a designed stepwise training program in a virtual learning environment. These systems typically assume that the student's intial and current knowledge states are known. Given the initial and current states of expertises one can give feedback about the areas of improvement for the student. However, if such tutoring, or coaching systems are applied in online use for tutoring the operators of an industrial process, it is not feasible to assume that there is knowledge available about neither the initial knowledge state nor the experience gained since. Therefore, a solution which is able to give feedback about the sources of improvement potential to the student, regardless about the prior knowledge of the student's level of expertise is needed.

This paper approaches the problem from a control engineer's point of view. The human operator is regarded as the central part of the man-machine system. To optimize the overall performance of the system, the goal in the improvement of operator skills should be the full utilization of the machine performance. The approach involves the following steps:

i. Modeling productivity regarding the task performance metrics available
ii. Determination of the most significant improvement potential sources based on the current productivity and the task performance metrics
iii. Presenting the feedback to the operator
iv. Assessment of the efficiency of the feedback

This paper proposes a solution for the first step and gives a guideline of how the second step could be approached on the basis of the gradient of the productivity model. Moreover, the use of the corrective feedback recommendation for comparing the operators' work styles is described. The third and fourth steps are left for future work.

This paper is organized as follows. First, the cut-to-length forest harvester is introduced and the operator work is described in order to give an idea about the challenges in operating the machine. The reseach problem of this paper is introduced in Section 2. The solution proposals to the problems are given in Section 3. The experimental results are presented in Section 4. The conclusions are presented at the end of the paper.

2. PROBLEM STATEMENT

Mechanized timber harvesting can be divided into two main categories by means of how the stems are processed in the forest, namely full-tree and cut-to-length methods. In Scandinavia, the most common is the cut-to-length method where trees are felled, delimbed and bucked [1] at the logging site with a forest harvester. The value of the stem is maximized by an optimization system which assists in bucking by suggesting the optimal cutting points. The value of the log depends on its grade, that is, the intended use of the log as end product. For example, the stock logs can end up to be sawn to planks in sawmills and the pulp logs are processed to pulp in pulp mills. The grade of the log depends e.g. on its dimensions. A forwarder carries the logs to the roadside for further transportation. It also sorts the logs into distinct piles by their grades in order to enhance the effectiveness of the whole logistic chain. A cut-to-length forest harvester is shown in Fig. 1.

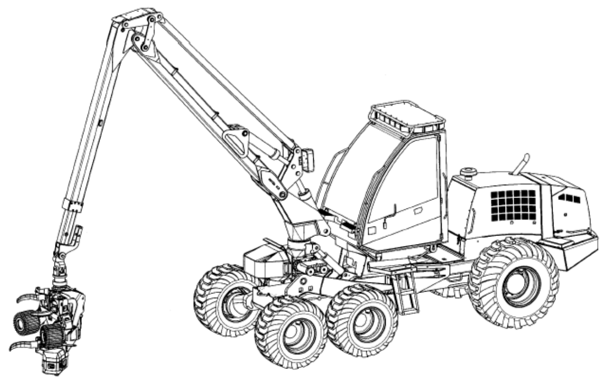

Fig. 1. A cut-to-length forest harvester. (Anon [2007])

Operating with the forest harvester requires good motor-sensory, decision making and problem solving skills. The operator needs to be familiar with the control system, be able to make fast decisions, and plan the work such that it is accomplished with minimal amount of non-value-adding motions and actions. The varying operating conditions such as tree sizes, weather and terrain conditions make the operator's work even more challenging. Because the work is very complex, the working styles between two operators may differ considerably. Each of the styles has pros and cons. One style can lead to better productivity but the cost can be the loss of fuel efficiency, for example.

Currently professional operators do not get any other feedback about their work than the resulting overall productivity of their work. They can get the information about their relative productivity level compared to statistical reference levels, but not the information about their work style or the work areas that their performance might be low. The operator's performance can be measured online in task level. The objective of this paper is to find a dependency between performance variables measured online and the productivity of the machine in different operating conditions. Based on the productivity model, it is possible to give instructions to the operator where to focus

[1] Bucking is cutting the trees to logs with desired lengths.

when trying to achieve better productivity. In addition, the instructions can be used to analyze the operator's performance and work style.

3. PROPOSED SOLUTION

Assume that there are N variables which describe the performance of the human operator in various tasks. Let those variables be denoted by x_i, where $1 \leq i \leq N$, which can be collected into vector $\mathbf{x} = (x_1, x_2, \ldots, x_N)$. Furthermore, it is assumed that there are M variables describing the prevailing operational conditions. Let them be denoted by vector $\boldsymbol{\xi} = (\xi_1, \xi_2, \ldots, \xi_M)$. If the productivity is denoted by y a mapping f from performance metrics and operational conditions can be constructed as

$$y = f(\mathbf{x}; \boldsymbol{\xi}), \tag{1}$$

which is assumed to be differentiable. A semicolon ";" is used to emphasize the difference between the input performance values $\mathbf{x}$ and input parameters $\boldsymbol{\xi}$. The parameters might include, for example, a separate model f for each distinct operating point.

By using the performance variables $\mathbf{x}$ and the operational conditions $\boldsymbol{\xi}$ an expert operator can be defined. The expert operator represents the "optimal" performance in the given operational conditions. If the productivity of the system can be modeled by (1), the values of the task performance metrics to achieve the optimal productivity are found by an inverse mapping f^{-1}. However, if the mapping is not linear, the inverse can be hard to define analytically. In addition, since there are more inputs than outputs several combinations of inputs can lead to the same output. Therefore, it is not important to give exact target values for the input. It is enough that the performance is at desirable level. Formally, the productivity of the expert operator in operating conditions $\boldsymbol{\xi}$ is found by

$$y_{\text{expert}} = \max_{\mathbf{x}} f(\mathbf{x}; \boldsymbol{\xi}) \tag{2}$$

In this paper the productivity of the expert operator is 90 percentile productivity limit as a function of $\boldsymbol{\xi}$ computed over the whole database.

3.1 ANFIS model for productivity

The first challenge is to solve the mapping (1), which gives the relation between the operational conditions, task performance metrics, and the productivity. In this paper, an ANFIS type fuzzy model is used to model productivity. A fuzzy model was chosen because it can deal with nonlinearity and the interpretation of the model is easier than, for example, conventional neural networks. An additional advantage is the availablity of powerful tools to build the fuzzy models. The structure of an ANFIS system is shown in Fig. 2. The inputs x_i are fuzzified based on the fuzzy sets A_{ik}. The rule premises are evaluated with the product operator giving weights w_i. The weights are normalized to sum up to unity in the N layer. The final ouput of the system is the weighted sum of the linear output layer activation functions of inputs x_i. (Jang [1993])

The fuzzy model is initialized by using the subtractive clustering method described in Section 3.2. After obtaining the initial rulebase and membership functions, the parameters

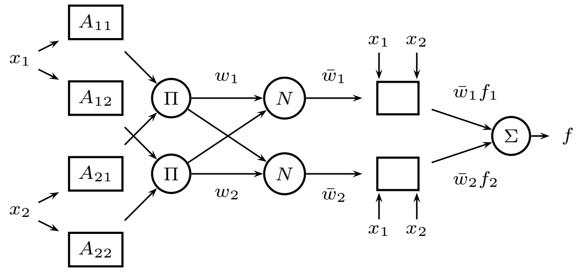

Fig. 2. Structure of an ANFIS fuzzy system with two inputs. (Adapted from Jang [1993])

of the fuzzy model are trained by using the hybrid training algorithm. The algorithm is described in Jang [1993].

$$\begin{aligned}\hat{y}(\mathbf{x}; \boldsymbol{\xi}) &= \frac{\sum_{k=1}^{K} w_k(\mathbf{x}; \boldsymbol{\xi}) f_k(\mathbf{x}; \boldsymbol{\xi})}{\sum_{k=1}^{K} w_k(\mathbf{x}; \boldsymbol{\xi})} \\ &= \sum_{k=1}^{K} \bar{w}_k(\mathbf{x}; \boldsymbol{\xi}) f_k(\mathbf{x}; \boldsymbol{\xi}),\end{aligned} \tag{3}$$

where $w_k(\mathbf{x}; \boldsymbol{\xi}) = \prod_{i=1}^{N} \mu_{A_{ik}}(x_i)$. Thus, the output value is the weighted sum of the (linear) functions f_i and the weights are obtained by evaluating the inputs over the rulebase.

In order to decide what are the most significant potential areas of improvement the gradient of the estimator is needed to be defined. The input membership functions are differentiable and the output membership functions are linear. Hence, the gradient becomes

$$\nabla_x \hat{y}(t) = \left(\frac{\partial \hat{y}}{\partial x_1}, \frac{\partial \hat{y}}{\partial x_2}, ..., \frac{\partial \hat{y}}{\partial x_N} \right), \tag{4}$$

where ∇_x describes the gradient of the estimator with respect to the performance variables $\mathbf{x}$. The operating conditions are assumed to remain constant. The partial derivatives are obtained using the chain rule for each layer of the ANFIS network similarly with the derivation of the training rule in Jang [1993].

3.2 Subtractive clustering

The description of the subtractive clustering algorithm follows one presented by Chiu [1996] except for the notation. Let $\mathbf{x}_i$ describe the i^{th} feature vector. Suppose that there are N feature vectors in total to be clustered. The data is assumed to be scaled such that each value is inside a unit hypercube. At the beginning each feature vector is considered as a cluster center. A measure for the potentiality of the i^{th} feature vector to serve as a cluster center is defined as

$$P_i = \sum_{j=1}^{N} e^{-\alpha \|\mathbf{x}_i - \mathbf{x}_j\|^2}, \tag{5}$$

where, $\alpha = \frac{4}{r_\alpha^2}$ and r_α is a positive constant. Let κ_r denote the reject ratio, that is, the ratio defining the minimum potential fraction of the first cluster which is accepted as new cluster center. Moreover, let κ_a denote the maximum potential fraction of the first cluster below which a new feature vector is accepted as a new cluster center. The k^{th}

cluster center is denoted by $\mathbf{x}_k^*$ and its potential by P_k^*. The cluster potentials are revised by

$$P_i \Leftarrow P_i - P_k^* e^{-\beta \|\mathbf{x}_i - \mathbf{x}_k^*\|^2}, \qquad (6)$$

where $\beta = r_\beta \alpha$.

Initialization: Set the first cluster center as
$P_1^* = P_{\arg\max_{1\le i\le N} P_i}$ and
$\mathbf{x}_1^* = \mathbf{x}_{\arg\max_{1\le i\le N} P_i}$
Do
  For all cluster centers $1 \le k \le K$
    For all feature vectors $1 \le i \le N$
    $P_i \Leftarrow P_i - P_k^* e^{-\beta \|\mathbf{x}_i - \mathbf{x}_k^*\|^2}$
    If $P_i \ge \kappa_a P_1^*$
      $K \Leftarrow K + 1$
      $\mathbf{x}_K^* \Leftarrow \mathbf{x}_i$
      $P_K^* \Leftarrow P_i$
While $P_K^* \ge \kappa_r P_1^*$

The algorithm has converged once the potentials of all feature vectors are within a certain fraction of the potential of the first cluster. The advantage of the algorithm is that it quite easy to implement and that it is not necessary to know the number of cluster centers beforehand. Therefore, it is suitable for providing the initial membership functions and rulebase for a fuzzy system.

3.3 Corrective feedback algorithm

As the objective is to optimize the productivity of the machine, a solution would be to find a sequence of corrective actions to increase the productivity. If formulated as such, a reasonable solution to find a route towards better productivity is to use the gradient descent method. Letting $\mathbf{x}(t)$ denote the measured value for performance vector at t, the local objective value $\mathbf{x}^{\text{Objective}}$ can be obtained by adjusting the performance variables to the direction of the gradient of the estimated performance. That is,

$$\mathbf{x}^{\text{Objective}}(t+1) = \mathbf{x}^{\text{Measured}}(t) + \gamma(t)\nabla_x \hat{y}(t), \qquad (7)$$

where $\gamma(t)$ denotes the updating step size at t and $\nabla_{\mathbf{x}} \hat{y}(t)$ the gradient of the estimated performance with respect to $\mathbf{x}$.

Since the feedback algorithm is based on the gradient of the estimated productivity, it is reasonable to ensure the validity of the estimate before defining the feedback. Thus, the updating step size is made to depend on the estimation error $e(t) = y(t) - \hat{y}(t)$. If $e(t)$ is large, the estimate is not reliable and no feedback is given.

(1) Evaluate the improvement potential, that is, the difference between current productivity $y(t)$ and the expert $e_{expert}(t) = \min(y_{\text{expert}} - y(t), 0)$. If $e_{\text{expert}}(t) > 0$ then go to the second step. Otherwise go the the last step.
(2) Estimate productivity using (3).
(3) Evaluate the gradient of the estimate using (4).
(4) Evaluate the estimation error $e(t) = y(t) - \hat{y}(t)$. If $|e(t)| < e_{\min}$ set $\gamma(t) = g(y(t), y_{\text{expert}})$ otherwise $\gamma(t) = 0$. [2]
(5) Set the new objective values for the performance variables according to (7).
(6) Set $t = t + 1$ and go to the first step.

[2] $0 \le g(\cdot) \le 1$ decreases as e_{expert} decreases.

The algorithm is applied such that the time instant t describes a suitable period of time, for example, one work shift. The mapping f needs to be smooth with respect to the parameters $\mathbf{x}$ so that the gradient can be computed. In addition, if there are local minima, the productivity might be in non-acceptable level, but the feedback is not given since the gradient is zero. This should be taken into account in the implementation of the algorithm. However, in this paper the challenge of local minima is not discussed.

3.4 Comparison of operator's work styles

The gradient vectors given by the corrective feedback algorithm can also be used to analyze the operators' work styles. The rationale for this is that if the algorithm suggests similar actions to two operators then, regardless of their productivity, they have same improvement areas and therefore also similar work styles. A natural similarity measure for two vectors with possibly different magnitudes is the cosine measure. For two vectors $\mathbf{v}_1$ and $\mathbf{v}_2$ the cosine similarity measure is defined by the cosine of the angle between the vectors, that is

$$d_c = \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{\|\mathbf{v}_1\|_2 \|\mathbf{v}_2\|_2}, \qquad (8)$$

where "$\cdot$" denotes the inner product and $\|\mathbf{v}_i\|_2$ the euclidean norm of the vector $\mathbf{v}_i$. The measure d_c is one if the vectors are parallel, zero if they are orthogonal and minus one if they are opposite. Therefore, the cosine similarity between the average gradient vectors of two operators describe the similarity of their work styles.

4. EXPERIMENTAL RESULTS

4.1 Experimental data

Working with the forest harvester varies depending on the market, that is, the geographical location of the workplace. Therefore, for this experiment only data from Finnish and Swedish stands were selected. In total, data from 13 operators were selected for this experiment. Several quantities about the performance in various tasks, and productivity in diferent operating conditions were calculated for each work shift, i.e. each eight hour period of work.

4.2 Modeling the productivity

The data gathered from each operator were gathered into vectors describing the productivity y, performance metrics $\mathbf{x}$ and the operational conditions $\boldsymbol{\xi}$. Half of the vectors were selected randomly to form the training data set. The remaining half of the data were split into validation and checking sets. The number of vectors in the whole data set was 3533 of which 1766 vectors were used for training, 883 vectors for checking, and 883 for validation.

The ANFIS model was initialized by using the subtractive clustering algorithm with parameters $r_\alpha = 0.5$, $r_\beta = 1.25$, $\kappa_r = 0.15$, and $\kappa_a = 0.5$. Two clusters were defined and thus the resulting ANFIS model had two rules. The input membership functions were Gaussian and the ouput membership functions linear. The model was trained using the training data described above. In addition, the checking data was used to determine the "early stopping" instant,

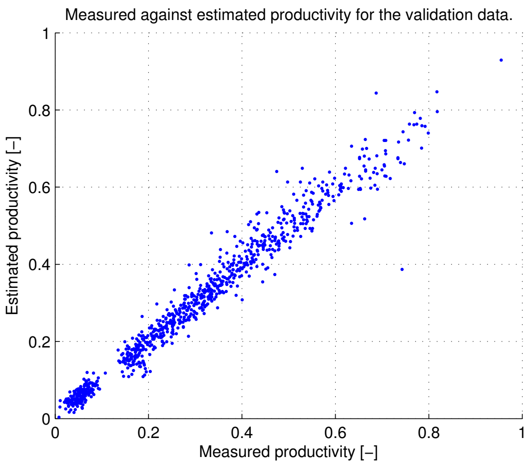

Fig. 3. Measured against estimated productivity for the validation data.

i.e. the iteration round which gives minimum value for the estimation error of the independent data set.

The model was validated by using a separate validation data set containing 1652 vectors. In Fig. 3, the true productivity and the estimated productivity given by the trained model are plotted against each other. The model seems to give good approximation for the productivity for the independent validation data set.

4.3 Operator analysis

The gradient based corrective action recommendation algorithm can also be used in offline analysis. One simply runs the algorithm for each work shift data vector and stores the respective recommendation values $\gamma(t)\nabla_x\hat{y}(t)$ of (7). Then by studying the distributions of the recommendation values the main improvement potential areas for the operator can be recognized.

Among thirteen operators, three were chosen for the improvement potential analysis. The improvement recommendations were computed for all work shift vectors of each operator. The results of the operator analysis are shown in Table 1. The relative productivity (RP) describes the ratio between the operator's average producrivity and the average productivity of all operators. So the greater RP the better the operator's productivity is in comparison with an average operator. The best operator is OP1. The algorithm does not suggest significant actions to improve the productivity, since it is already in a high level. OP1 should try to decrease the values of the variables $x_3 \dots x_7$ of which particularly x_5 should be focused on. Similarly for OP2, the algorithm suggests to decrease the values of $x_3 \dots x_7$ but especially x_3 and x_5 should be decreased. For the operator with the worst productivity, OP3, the algorithm suggest significant actions. He/she should pay attention to to increase the values of $x_1 \dots x_3$. In addition, the values of x_4, x_6 and x_7 should be significantly decreased to improve the productivity.

In addition to the improvement potential analysis, also the work styles of the three operators were compared against each other. The average gradient vectors were computed for each operator, which were used to obtain the cosine

Table 1. The relative productivities and the improvement recommendations for the operators performance variables given by the gradient algorithm. The number of plus/minus signs describes the level the value of the performance metric should be increased/decreased. Nothing needs to be done if the cell is empty.

	OP1	**OP2**	**OP3**
RP	1.729	1.113	0.666
x_1			+++
x_2			+++
x_3	-	- -	+++
x_4	-	-	- - -
x_5	- -	- -	- -
x_6	-	-	- - -
x_7	-	-	- - -

Table 2. Operator work style analysis with the cosine similarity between the operators' average gradient vectors.

	OP1	**OP2**	**OP3**
OP1	1.000	0.957	0.437
OP2	0.957	1.000	0.303
OP3	0.437	0.303	1.000

measures d_c using (8). The values of d_c between the average gradient vectors of the operators are shown in Table 2. One can easily note that the operators OP1 and OP2 have similar work styles, of which OP3 differs considerably. The result feels reasonable since the productivity of OP3 is very low. Therefore, it is likely that the skills of OP3 are not in the same level as OP1 or OP2.

4.4 Simulation of the gradient descent algorithm

The performance optimization algorithm was simulated based on the models (3) and (2). The expert operator's productivity was defined as the 90^{th} percentile value of productivity in each operational conditions. The updating step size was defined as a sigmoid function whose value decreased to zero as the obtained performance approached expert's performance.

The simulation proceeds as follows. A sample $\mathbf{x}$ with low respective productivity y was chosen as initial value. The productivity was estimated using (3). The gradient with the performance variables was estimated using (4). The gradient-based updating rule (7) was evaluated. However, since it is not reaslistic to assume that the operator's skills would develop ideally, the operator's performance was increased with probability 0.1. If a uniform random number obtained a value greater than 0.9, the new objective values for the productivity were obtained. Because the simulation does not include the model about operator's behavior and comprehension of the feedback, the new objective values for the performance variables were set directly as the new performance values. Thus, the simulation result presented here is just simulation of the gradient-descent algorithm which naturally converges towards the optimum. The result of an imaginary performance development in the simulation is shown in Fig. 4. At each time instant t a new objective value was computed using (7). The simulation was stopped when the performance is close enough to the level determined by an expert operator model (2).

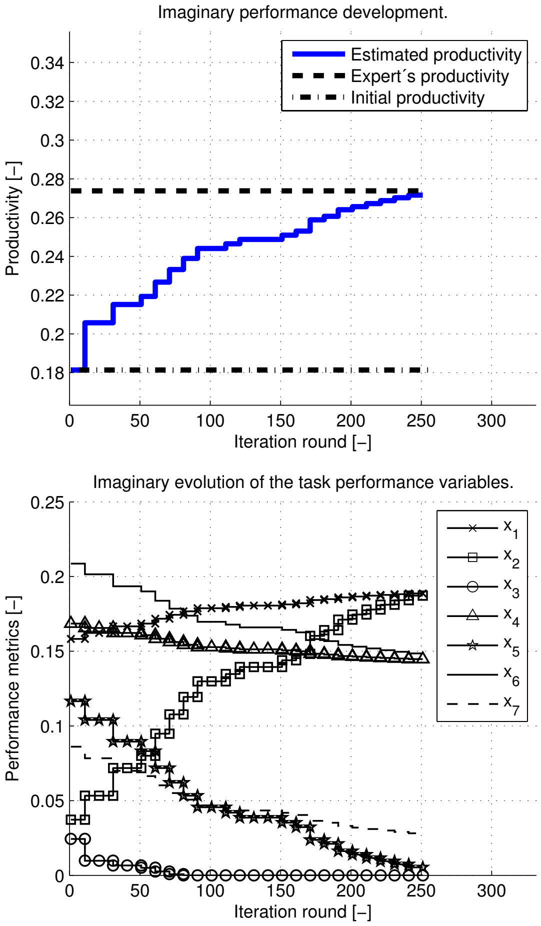

Fig. 4. An illustrative simulation results for an imaginary performance development of the operator and the evolution of the task performance variables during the simulation.

The evolution of the task performance variables during the simulation is shown in the second plot of Fig. 4. The values of the variables x_1 and x_2 increase throughout the simulation whereas values of $x_4 \ldots x_7$ decrease. In the beginning, the value of x_3 first slightly increases and then drops back to zero. The simulation shows that the performance variables not only have impact on productivity but have also mutual dependencies. The operating point was constant during the simulation, but in practice this is not the case. Tree sizes, weather conditions, and stand properties vary, which makes every processing situation unique and causes severe noise to the measurements. Therefore, in practice the operator's performance should be filtered so that only the change in the average performance would change the objective values.

5. CONCLUSIONS

An ANFIS model for the productivity of a forest harvester was proposed. In addition, an algorithm which can give feedback about the most significant areas of improvement in the operator's actions to improve the productivity of the machine was developed. The productivity model was trained and validated using real processing data gathered from several machines with several operators. It was shown how the operators' performance and work style can be analyzed offline by the gradient-based approach. The idea of the feedback algorithm was shown by using a simple simulation.

The inputs of the productivity model in this paper were mostly time metrics describing the performance in different work tasks. The gradient-based approach gives a description about the sources of improvement potential but it does not provide direct guideline of how the operator can achieve the expert level. On the other hand, the mere existance of objective values has encouraged some operators to improve their performance. A motivated operator finds a way to do it as long as there is a reference to compare to. In addition, the utilization of the gradient-based feedback algorithm needs further solutions for several challenges. How to present the feedback to the operator? Does the feedback increase performance? Nevertheless, the results presented in this paper are encouraging and provide a basis to tackle with the further challenges.

Yet another point which is needed to emphasize is that mere productivity optimization is not feasible. One needs to consider the overall efficiency of the process being optimized. The overall efficiency is a tradeoff between productivity, fuel economy and quality of work. One could, for example, attach the three quantities into a cost function to minimize the total cost.

REFERENCES

Anon. John Deere: http://www.deere.com/fi_fi/, August 2007.

L.H. Chiang, E.L. Russel, and R.D. Braatz. *Fault Detection and Diagnosis in Industrial Systems*. Springer-Verlag London Limited, 2001.

Stephen Chiu. Method and software for extracting fuzzy classification rules by subtractive clustering. In *Proceedings of the Fuzzy Information Processing Society, 1996, NAFIPS Biennial Conference of the North American*, Berkeley, CA, USA, June 1996.

Ujita Hiroshi, Yokota Takeshi, Tanikawa Naoshi, and Mutoh Keiko. Computer aided instruction system for plant operators. *International Journal of Human – Computer Studies*, 45:397–412, 1996.

Jyh-Shing Roger Jang. Anfis: Adaptive-network-based fuzzy inference system. *Systems, Man and Cybernetics, IEEE Transactions on*, 23(3):665–685, 1993.

B. Ozdemir and F. Alpaslan. An intelligent tutoring system for student guidance in web-based courses. In *Fourth International Conference on Knowledge-Based Intelligent Engineering Systems and Allied Technologies*, 2000.

S. Ryynänen and E. Rönkkö. Productivity and expenses associated with thinning harvesters. Technical report, TTS-Institute, 2001. (In Finnish).

M. Sirén. One-grip harvester operation, its silvicultural result and possibilities to predict tree damage. Technical report, Finnish Forest Research Institute, 1998. (In Finnish).

Kari Väätäinen, Heikki Ovaskainen, Pekka Ranta, and Antti Ala-Fossi. The significance of the tacit knowledge of the forest harvester operator at working point level. Technical report, Finnish Forest Research Institute, 2005. (In Finnish).