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EVALUATION OF UNCERTAINTY IN ESTIMATED TRACTIVE EFFICIENCY FROM MEASURED TRACTOR PERFORMANCE PARAMETERS

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ABSTRACT

Knowledge of uncertainty in tractor performance parameters assists in estimating uncertainty in tractive efficiency. Average values of the performance parameters (axle torque, drawbar pull, wheel speed, and actual speed) when the tractor was used to pull a load unit on an asphalt surface were used as base values in the evaluation of the uncertainty of the tractive efficiency. Average performance parameters were 5.28 kN·m, 2 kN, 5.36 km/h, and 5.22 km/h, respectively, and their standard deviations were 0.56 kN·m, 0.40 kN, 0.03 km/h, and 0.01 km/h, respectively. First order approximation was used to quantify the uncertainty in estimated tractive efficiency from the performance parameters of an instrumented tractor. A sensitivity analysis was also performed as a part of the uncertainty analysis to identify the tractor performance parameter that has the greatest effect on tractive efficiency. All parameters significantly affected tractive efficiency and were used in the uncertainty analysis. Actual tractor speed contributed approximately 0.05% of the total uncertainty in terms of variance. Tractor wheel speed, tractor pull, and axle torque contributed approximately 0.13, 86.60, and 13.22% of the uncertainty, respectively. As a result, it is clear that the drawbar pull measuring device should receive more effort to refine its outcome, and thus improve the tractive efficiency.

Key words: *sensitivity, tractive efficiency, uncertainty.*

1. INTRODUCTION

Uncertainty associated with tractive efficiency estimates is often of critical importance. The numerical values of tractor performance parameters measurements are a subject to a certain degree of uncertainty due to inherent random errors of the measurement system. If a small change in a measured parameter results in a relatively large change in the outcome, the outcome is said to be sensitive to that parameter. Sensitivity analysis measures the impact of alternate values of uncertain parameters on the output response. The parameter to which the outcome is most sensitive should be measured very accurately to reduce its uncertainty.

Perret *et al*. (1997) described and evaluated two methods for analyzing uncertainty in agricultural system design. The methods were the first- and second-order analysis, and the fuzzy logic. The two approaches were used to quantify the expected variability of the dependent variable and its variance for both steady- and non-steady-state drainage designs. Their results indicated that both approaches can provide the designer with an indication of reliability of the estimates, a way of selecting a design option which meets a specified probability of success, as well as a means of comparing the relative importance of uncertainty in various input parameters. Zhang and Haan (1996) evaluated the uncertainty in estimated flow and phosphorus loads by a computer model. They demonstrated how uncertainty in output from the model is assessed based on uncertain knowledge about input parameter values. Also, the study showed how to identify input parameters that were the largest contributors to the uncertainty.

Al-Hamed (2001) performed a sensitivity analysis on the prediction model of tractive efficiency for three input parameters: wheel slip, dynamic wheel load, and tire deflection. The inputs were ranked from the most important to the least. Corresponding to the base values (wheel slip = 0.10; wheel load = 17 kN; tire deflection = 7 cm), wheel load had the highest relative coefficient of -0.146, whereas wheel slip had the lowest relative coefficient of -0.029 because the model result was near its maximum value. However, the model was highly sensitive to wheel slip when its values were varied ±0.05 from the given base values.

The tractive efficiency (TE) of a driven tire was defined as the ratio of the output power to input power (ASABE Standards, 2006). Thus, the tractive efficiency is calculated as:

$$TE = \frac{Drawbar\ Power}{Axle\,Power} = \frac{P\,V_a}{T\,\left(V_t/r\right)} \qquad (1)$$

where
P = tractor drawbar pull, N
V_a = actual travel speed, km/h
V_t = tractor wheel speed, km/h
r = rolling radius, m
T = axle torque, kN.m

For the uncertainty analysis, performance parameters from an instrumented Massey Ferguson (MF) 3090 tractor were used. The instrumentation system to measure tractor pull, axle torque, actual speed, wheel speed, and other performance parameters of the instrumented tractor were discussed in Al-Suhaibani *et al*. (1994), Al-Janobi and Al-Suhaibani (1996), and Al-Janobi *et al*. (1997). Knowledge of uncertainty in parameter values leads to determination of uncertainty in tractive efficiency estimates. Investigation of the uncertainty in the parameters is needed to decide which input parameters should receive more effort to refine their outcomes.

The objective of this research was to evaluate the uncertainty of the estimated tractive efficiency of an instrumented tractor. Specifically, the goal was to perform sensitivity analysis to rank the tractor input parameters based on their importance, and then perform uncertainty analysis on them to investigate their impact on the tractive efficiency estimates.

2. MATERIALS AND METHODS

2.1. Uncertainty analysis

Uncertainty associated with tractive efficiency estimates is evaluated through the knowledge of uncertainty of tractor performance parameters and their impact on tractive efficiency. The input parameters of interest as shown in Equation (1) are tractor drawbar pull, actual travel speed, tractor wheel speed, and axle torque. The rolling radius was not considered in this study, and was assumed to have a constant value (0.825 m) for a given tire size, inflation pressure, and load. The uncertainty evaluation was conducted for certain performance parameters of the MF 3090 instrumented tractor equipped with 18.4R38 single rear tires. Average values of the parameters when the tractor was used to pull a load unit on an asphalt surface were used as base values as shown in (Table 1). Tractor wheel slip the was 3%, and was less than expected wheel slip at the maximum tractive efficiency for the tractor on the given surface type. Therefore, tractive efficiency is expected to be affected greatly by changes in performance parameters.

Table (1): Parameters base values.

Parameter	Base value	
Axle torque	5.28	kN·m
Wheel speed	5.36	km/h
Drawbar pull	2.00	kN
Actual speed	5.22	Km/h
Rolling radius	0.825	m

Sensitivity analysis was needed as a part of the uncertainty analysis, and was performed on tractive efficiency relative to the input parameters. The sensitivity was calculated as the partial derivative of the tractive efficiency as a function of each input parameter at its specified base value. Absolute and relative sensitivity coefficients were calculated using the equations of Haan and Zhang (1996), and Zhang and Haan (1996), as follows:

$$S = \frac{\partial\, TE}{\partial\, p_i} \qquad (2)$$

$$S_r = S \cdot \frac{p_i}{TE} \qquad (3)$$

where
S = absolute sensitivity (output units/input units), which measures the change in TE per unit change in input parameter, p_i.
S_r = relative sensitivity (dimensionless).

These coefficients can be compared on the input parameters and used to rank them in terms of sensitivity values. Sensitivity coefficients were numerically determined at base values of the parameters. Numerical derivatives were used to approximate the partial derivatives of Equation (2). The numerical partial derivatives were obtained from the relationship (Haan and Zhang, 1996 and Zhang and Haan, 1996) as:

$$\frac{\partial\, TE}{\partial\, p_i} = \frac{TE_{p_i+\Delta p_i} - TE_{p_i-\Delta p_i}}{2\,\Delta p_i} \qquad (4)$$

where the increment of input parameter, Δp_i, was taken as 10% of each parameter base value. For each input parameter, the sensitivity coefficients were calculated for $p_i \pm \Delta p_i$, while all other parameters were held at their base values. The relative sensitivity coefficients identified the most sensitive input parameter.

Table (2): Statistical analysis of the input parameters.

Parameter	**SD$^\$$**	**Var***	**C.V.$^+$**
Axle torque	0.56	0.3106	10.57
Wheel speed	0.03	0.0011	0.62
Drawbar pull	0.40	0.1577	19.83
Actual speed	0.01	0.0002	0.25

$^\$$ - Standard deviation * - Variance $^+$ - Coefficient of variation

The uncertainty analysis was performed on the tractive efficiency relative to the input parameters using the method of first order analysis to show how parameter variability contributes to the output variability. Perret *et al*. (1997) derived the theoretical concepts of the first order analysis based on known variances of input parameters. The uncertainty is quantified in terms of variance of the input parameters. The variance of the tractive efficiency as a measure of uncertainty is the summation of variability contributions of input parameters (Haan and Zhang, 1996; Zhang and Haan, 1996 and Nam *et al*., 2009), and is expressed as:

$$\mathrm{Var\ (TE)} = \sum_{1}^{n} S_i^2 \ \mathrm{Var}(p_i) + 2 \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} S_i S_j \ \mathrm{Cov}(p_i, p_j) \qquad (5)$$

where S_i refers to the sensitivity coefficient with respect to the ith input parameter, p_i. For uncorrelated parameters, the covariance in the second term equals zero.

3. RESULTS AND DISCUSSION

An uncertainty analysis was performed on the tractive efficiency estimates of the MF 3090 instrumented tractor equipped with 18.4R38 single rear tires operating on an asphalt surface. The method of first order approximation was used to quantify the uncertainty of the tractive efficiency estimates. Therefore, the contribution of each input parameter to the variability in estimated tractive efficiency was calculated. For the determination of uncertainty, variance values of input parameters and the absolute sensitivity coefficients were necessary. A statistical analysis was performed on the input parameters data to determine the variances. (Table 2) shows the standard deviation values, variance values, and the coefficient of variations of the input parameters. The fluctuation of the input parameters is shown in Figures 1, 2 and 3.

Traction tests conducted by researchers indicated that axle torque increases linearly with applied draft. However, lack of correlation among performance parameters was expected if a tractor was operated at a constant condition. A correlation structure among the parameters was estimated, and it showed that some parameters were correlated, as shown by the correlation matrix (Table 3). Correlations greater than 0.260 are significant at $P < 0.05$, and correlations greater than 0.323 are significant at $P < 0.01$. Hence, the variance of the tractive efficiency estimates, as a measure of uncertainty in Equation (5) is applicable.

The sensitivity of the tractive efficiency results, relative to the input parameters, was determined simultaneously. All input parameters were of equal importance on the sensitivity of the tractive efficiency, as shown by the closeness of the numerical values of relative sensitivity to one another (Table 4). This implies that all inputs should receive the same efforts to refine their outcomes. Negative signs on sensitivity coefficients indicate that tractive efficiency decreases with increases in input parameters.

The uncertainty analysis shows the impact of the variability in the input parameters on the tractive efficiency estimates. The variance values of tractive efficiency corresponding to each input parameter were calculated, and are presented in (Table 5). Actual tractor speed contributed approximately 0.05% of the total uncertainty on the tractive efficiency estimates in terms of variance. Tractor wheel speed and axle torque contributed approximately 0.13 and 13.22% of the total uncertainty respectively, whereas the major contribution of uncertainty was from the parameter tractor drawbar pull with 86.60% of the total uncertainty. The variations in wheel speed values resulted from the presence of inherent random errors in the measuring system as the tractor was operated at a constant speed, whereas the variations in the other input parameters were due to the presence of random errors as well as possible variations in soil strength in the field.

The results of this paper apply to the implemented traction parameter measurement system. Other systems may have different results. However, the methodology applies to any traction monitoring system.

4. CONCLUSION

The uncertainty in estimated tractive efficiency of an instrumented MF 3090 tractor was evaluated. First order approximation was used to

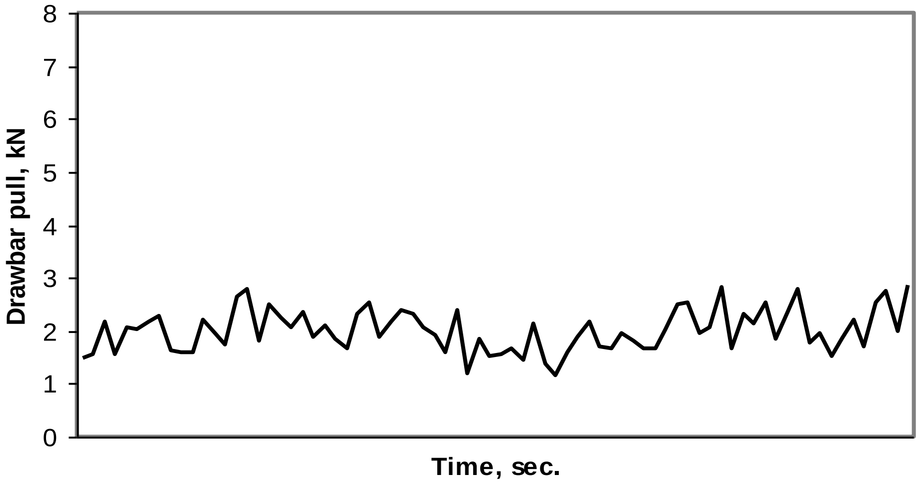

Fig. (1): Drawbar pull measurements.

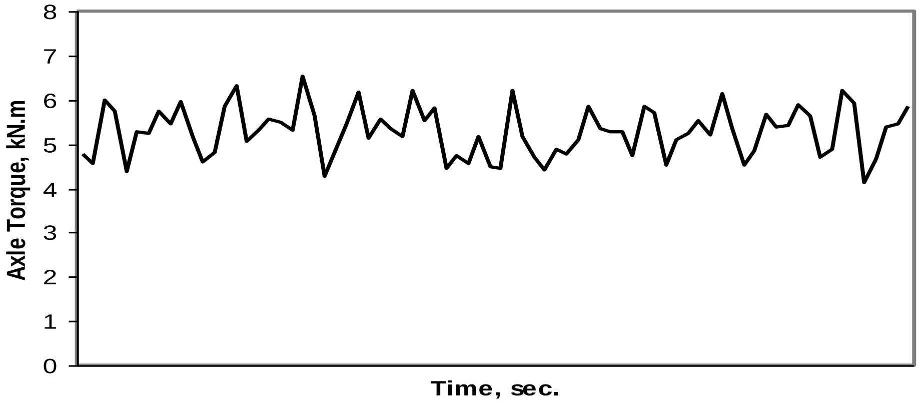

Fig. (2): Axle torque measurements.

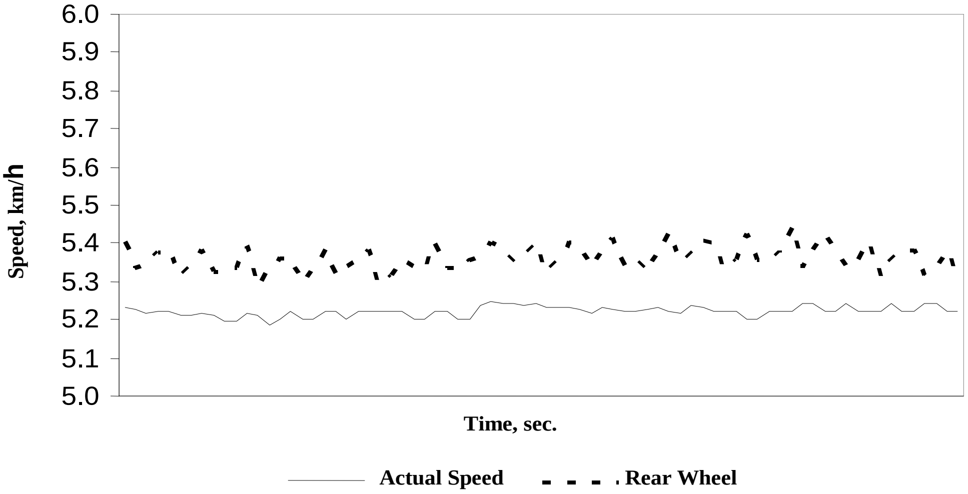

Fig. (3): Rear wheel and actual speeds.

Table (3): Correlation matrix for the performance parameters.

	Axle torque	Wheel speed	Drawbar pull	Actual speed
Axle torque	----	(0.135)	(0.008)	(0.011)
Wheel speed	-0.173	----	(0.357)	(0.017)
Drawbar pull	0.301	-0.107	----	(0.283)
Actual speed	-0.290	0.274	-0.125	----

* Lower left half of the table are Pearson correlation.
* Upper right half are (P-Value).

Table (4): Sensitivity coefficients.

Input Parameter	Sensitivity coefficient	Relative sensitivity
Axle torque	-0.058	-1.01
Wheel speed	-0.057	-1.01
Drawbar pull	0.152	1.00
Actual speed	0.058	1.00

Table (5): Uncertainty of tractive efficiency due to performance parameters.

Parameter	Var(TE)	Contribution, %
Axle torque	0.000470	13.22
Wheel speed	0.000005	0.13
Drawbar pull	0.003079	86.60
Actual speed	0.000002	0.05

quantify uncertainty in tractive efficiency estimates. Sensitivity coefficients and parameter variances were used to determine the uncertainty of tractive efficiency estimates. The sensitivity of tractive efficiency relative to the input parameters (tractor drawbar pull, axle torque, actual travel speed, and tractor wheel speed) was determined as part of the uncertaity evaluation. The sensitivity analysis showed that all inputs are of equal importance and significantly affected tractive efficiency. Actual tractor speed contributed approximately 0.05% of the total uncertainty in terms of variance. Tractor wheel speed, axle torque, and tractor pull contributed approximately 0.13, 13.22, and 86.60% of the total uncertainty, respectively. Thus, acquiring knowledge of these parameters has a significant impact on reducing the uncertainty in estimated tractive efficiency.

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تقييم عدم الثقة في كفاءة الشد المقدرة من متغيرات أداء الجرار الزراعي المقاسة

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ملخص

تساعد معرفة عدم الثقة لمتغيرات أداء الجرار الزراعي المقاسة في حساب عدم الثقة لكفاءة الشد. تم استخدام متوسط قيم متغيرات الأداء (العزم على محور العجلات، وقوة الشد، وسرعة العجلات، وسرعة الجرار الفعلية) عند سحب الجرار الزراعي لوحدة تحميل على سطح أسفلتي كقيم أساسية لتقييم عدم الثقة لكفاءة الشد. وكانت متوسطات متغيرات الأداء 5.28 كيلونيوتن·متر، و 2 كيلونيوتن، و 5.36 كم/س، و 5.22 كم/س، على التوالي. وكانت الانحرافات المعيارية 0.56 كيلونيوتن·متر، و 0.40 كيلونيوتن، و 0.03 كم/س، و 0.01 كم/س، على التوالي. ولتحديد عدم الثقة لكفاءة الشد المقدرة من متغيرات الأداء لجرار زراعي مجهز بأجهزة قياس تم استخدام التقدير ذو الدرجة الأولى. وتم أيضا إجراء تحليل الحساسية كجزء من تحليل عدم الثقة لتمييز متغير أداء الجرار الذي له التأثير الأكبر على كفاءة الشد. وتبين أن جميع المتغيرات تؤثر بشكل ملحوظ في كفاءة الشد وبالتالي استخدمت في تحليل عدم الثقة. ساهمت سرعة الجرار الفعلية تقريبا بنسبة 0.05٪ من عدم الثقة الكلية من حيث التباين. وساهمت سرعة العجلات للجرار الزراعي وقوة الشد والعزم على محور العجلات تقريبا بنسبة 0.13٪ و 86.60٪ و 13.22٪ من عدم الثقة، على التوالي. ويتضح من ذلك ضرورة بذل مزيد من الاهتمام بمقياس قوة الشد لتحسين نتائجه وبالتالي تحسين كفاءة الشد.

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