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A New Method and Model for the Estimation of Residual Value of Agricultural Tractors

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Abstract: The residual value of a tractor affects the cost of ownership. As there is not much transactional information available for used tractors, nor is there a history of new tractor prices, existing studies struggle to forecast the residual value of agricultural tractors. This is made even more challenging by the emission-regulation-related tractor price increase, low inflation in recent decades, and the complexity of the portfolio offerings from manufacturers. Using the new equivalent tractors, grouped by families of similar characteristics, bypasses these challenges and enables us to obtain larger data sets. These large data sets can be forecasted using transparent linear power regressions that offer the lowest root mean squared error (RMSE = 1.5574) and the highest combined, adjusted coefficient of determination (RSqAdj = 0.8457), outperforming all previously tested studies as well as the ensemble, Gaussian process regression, kernel, linear regression, neural network, support vector machine, and decision tree models. The accessibility of the public information required, as well as its processing using mainstream software through a model that is simple to use, yet robust, enables any stakeholder (manufacturers, sellers, financers, insurers, and, most of all, users) to reliably determine the residual value of an agricultural tractor, empowering them to make fact-based, cost-of-ownership-optimized decisions.

Keywords: agricultural tractors; previously owned; secondhand; residual value; depreciation; cost of ownership; cost of operation

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1. Introduction

The operating and ownership costs of machines often comprise more than half of the total crop production costs. Minimizing the machinery portion of the production costs requires a routine assessment of the benefits and costs associated with owning, leasing, or renting machinery [1].

Most farm equipment is still acquired under a conventional purchase plan. The capital may come from the purchaser's own funds, a third-party lender, or a company financing plan. However, an increasing number of major machinery items are being leased, via operating lease (in which the user can tax-deduct the payments as the machine belongs to the financer), via finance lease (in which the user owns the machine and is therefore entitled to take depreciation deductions) or by using a rollover purchase (in which the operator purchases a new or nearly new piece of equipment from a dealer with the expectation that it will be exchanged for another model after one year or season) [2].

Whether a tractor was paid for upfront, used equipment was traded as a payment in kind, or the machinery was traditionally financed, leased, or rented, the residual value has a tremendous impact on the finance cost, as the financer will ensure that the loan's lien is below the residual value [3]. If the residual value is uncertain, the financer will include a haircut [4] as a safety factor that renders the finance scheme more expensive to the purchaser.

1.1. Previous Studies

Out of all agricultural machinery, the tractor is a key element in farm/ranch mechanization as most agricultural tasks rely on it, due to its capacity to pull (and push) and take off power (mechanical, hydraulic, and/or electrical) [5]. Therefore, the investment a tractor represents one of the most important investments in both number and value.

Peacock and Brake [6] demonstrated that standard accounting techniques do not adequately reflect the economic deprecation of farm machines. European tax depreciation methods vary tremendously between countries [7], and do not reflect economic depreciation.

Therefore, the importance of a deep understanding of the depreciation rates of agricultural tractors is paramount. Ample research has been conducted on the matter, including the following studies: in the U.S.A., Bradford [8], Musser, Tew, and White [9], Reid and Perry, Bayaner, and Nixon [8], Weersink and Staube [10], Cross and Perry [11,12], Unterschultz and Mumey [13], Dumler, Burton, and Kastens [14,15], Wu and Perry [16], ASABE [17], and Kay, Edwards, and Duffy [18]; in the UK, Williams [19], Cunningham, and Turner, [20], Wilson and Davis [21], Wilson and Tolley [22], and Wilson [23]; in Canada, McNeill [24], Hansen and Lee [25], Witte, Back, Sponagel, and Bahrs [26]; and in Spain, Fenollosa Ribera and Guadalajara Olmeda [27] and Ruiz-Garcia and Sanchez-Guerrero [28].

The depreciation studies defy the challenge by executing regression analyses, which accurately describe the problem as a function of multiple, independent variables. However, different approaches were undertaken by the authors. For example, Wu and Perry [16], ASABE [17], and Kay, Edwards, and Duffy [18] concurred that the independent variables of age, working hours, and engine power have a significant influence on the depreciation; Unterschultz and Mumey [13], Wilson and Tolley [22], Fenollosa Ribera and Guadalajara Olmeda [27], Wilson [23], and Witte, Back, Sponagel, and Bahrs [26] used data that included the tractor manufacturer; and Cross and Perry [11,12] included the care and condition of the tractor as well as additional features or regional influences.

The number of European used tractor sales [29] is small compared to the European passenger car industry [29]. Furthermore, the number of models and, even more so, the substantial number of options, make the statistical sample even more atomized. The difficulty is in accessing a large dataset, which is typically required for empirical studies [23]. In order to address this challenge, some studies, such as Cross and Perry [11,12], Unterschultz and Mumey [13], Dumler, Burton, and Kastens [14,15], Wu and Perry [16], ASABE [17]; Kay, Edwards, and Duffy [18], and Witte, Back, Sponagel, and Bahrs [28], were based on auction prices; others, such as Fenollosa Ribera and Guadalajara Olmeda [27], were based on transactional prices; and still others, such as Wilson and Tolley [22], Wilson [23], and Ruiz-Garcia and Sanchez-Guerrero [28], used advertised prices (Table 1).

Table 1. Details of previous studies.

Reference	Data Source	Data Size	Variables	Function
Peacock, D. L., and Brake, J. R. (1970).	U.S.A. Sales	-	Age	Linear
ASAE (1979).	U.S.A.	-	Age	Exponential
McNeill, R. C. (1979).	Canada	32	Age and state	Exponential
Leatham, D. J., and Baker, T. G. (1981).	U.S.A.	1454 tractors	Age, power, motor type, traction, and manufacturer	Exponential
Reid, D. W., and Bradford, G. L. (1983).	U.S.A.	411	Age, power, motor type, manufacturer, increasing usage, and technological changes	Exponential
Perry, G. M., Bayaner, A., and Nixon, C. J. (1986).	U.S.A.	1612	Age, power, manufacturer, usage, care, and macroeconomic variables	Box–Cox
Hansen, L., and Lee, H. (1991).	Canada	-	Age, year of manufacture, and purchase year	Linear

Table 1. *Cont.*

Reference	Data Source	Data Size	Variables	Function
Cross, T. L., and Perry, G. M. (1995).	U.S.A. Auctions	-	Age, usage, manufacturer, care, type of auction, region, and macroeconomic variables	Box–Cox
Unterschultz, J., and Mumey, G. (1996).	U.S.A. and Canadian Auctions	3202 Tractors	Age, manufacturer	Ratified by Hansen and Lee model
Cross, T. L., and Perry, G. M. (1996).	U.S.A. Auctions	433 <60 kW 1946 60–112 kW 866 >112 kW	Age, usage, manufacturer, care, and macroeconomic variables	Box–Cox
Wu, J., and Perry, G. M. (2004).	U.S.A. Auctions	657 30–79 hp 1420 80–120 hp 781 121+ hp	Age, production year, manufacturer, and other	Box–Cox
Fenollosa Ribera, M. L., and Guadalajara Olmeda, N. (2007).	E.S. Sales	7876 13–79 hp 3963 80–133 hp 731 134–263 hp Dec'99-Dec'02	Age, power, brand, and others	Ordinary Least Squares (OLS)
Wilson, P., and Tolley, C. (2004).	U.K. Adverts	968	Age, hours, power, brand, and others	Ordinary Least Squares (OLS)
Wilson, P. (2010).	U.K. Adverts	1223	Age, hours, power, brand, and others	Ordinary Least Squares (OLS) Box–Cox
ASABE. (2011 (R2020)).	U.S.A.	-	Age, usage, and power	Box–Cox
Kay, R. D., Edwards, W. M., and Duffy, P. A. (2020).	U.S.A. Auctions.	-	Based on ASABE standards, 2006	Box–Cox
Witte, F., Back, H., Sponagel, C., and Bahrs, E. (2022)	German Adverts and Auctions	2667 tractors	Age, hours, power, and brand	Exponential
Ruiz-Garcia, L., and Sanchez-Guerrero, P. (2022).	EUR Adverts	227 new 1003 used	Age, hours, power, and brand	Robust linear (polynomic)

1.2. Current Issues

The portfolio offered by manufacturers has grown complex, to the point of offering, with the same engine power, several wheelbases, multiple transmission options and user interfaces, and different shipping and maximum permissible weights with. the same power. These factors have a tremendous impact on selling price (Table 2).

Table 2. Manufacturer's suggested retail price (MSRP) for 107 kW from one brand relative to the most economical offering.

Model Identifier	B I Hb I 006 *	B I Gb I 005 *	B I Ga I 005 *	B I Eb I 001 *	B I Ea I 001 *
Rated Power	107 kW				
Wheelbase	2525 mm	2564 mm			2820 mm
Shipping Mass	5300 kg	6940 kg			7470 kg
Max Mass	9000 kg	10,250 kg			10,250 kg
Transmission	Partial Powershift Transmission	Partial Powershift Transmission	Continuous Variable Transmission	Partial Powershift Transmission	Continuous Variable Transmission
MSRP relative to the most economical offering					
Classic Interface	1.00				
Advanced Interface	1.05	1.13		1.11	
Premium Interface	1.14	1.17	1.28	1.16	1.34
Ultimate Interface		1.22	1.33	1.21	1.39

* Brand, family, and model are anonymized to avoid any bias.

As these features result in different productivity, efficiency, maintenance, and repair requirements they enjoy (or suffer) different demands from the market. Consequently, they have different residual values, despite sharing the same engine power. Thereof, a study considering only the engine power might have challenges discerning the residual value between such different tractors sharing the same power.

The European Commission (EC) off-road diesel engine emission regulations [30–33] have had a tremendous impact on the lifespan of tractor series (Figure 1).

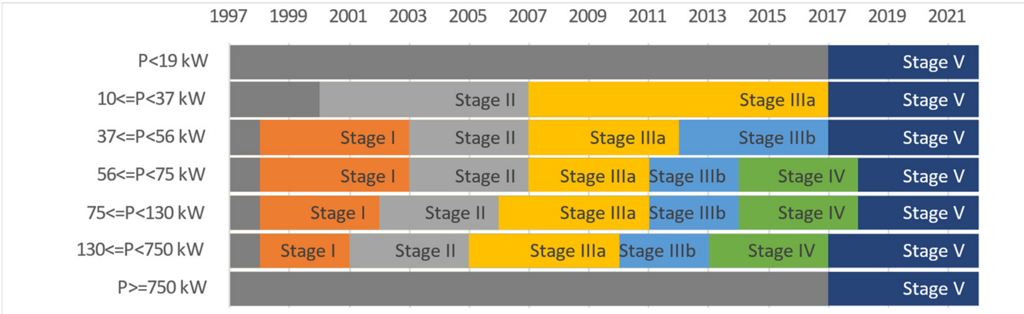

Figure 1. European off-road diesel engine emission regulations implementation by engine power.

The on-road diesel emission regulations have had an impact on the cost [34,35]. Despite the fact that the last European emission regulation has been already implemented, it is quite likely that new emission regulations will be implemented with their associated costs [36]. The off-road diesel engine emission regulations cost is even higher, as the fixed costs must be distributed amongst a much smaller number of engines (Figure 2).

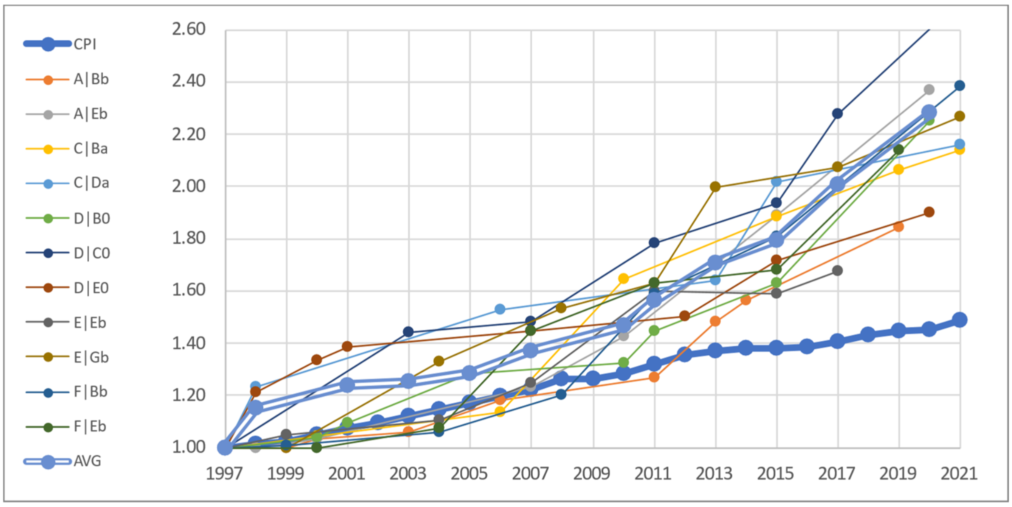

Figure 2. Eurozone harmonized index of consumer prices (HICP) and Germany's tractor family MSRP evolution relative to 1997.

1.3. Goal

The goal of this research is to develop a residual value calculation methodology that is accessible to all stakeholders (owners, users, marketeers, financiers, and insurers) and that finds a balance between simplicity of use and accurate results. This methodology will be applied to standard, agricultural cabbed tractors with more than 75 kW of horsepower from the main OEMs (Case IH, Claas, Fendt, John Deere, Massey Ferguson, and New Holland) in the main markets of Western Europe [37].

2. Materials and Methods

2.1. Dataset

Transactional European information does not exist in sufficient numbers to be properly analyzed [23]. The number, type, and condition of the European-auctioned machines are not aligned with standard market expectations. Therefore, this study considered agricultural tractors with an engine power higher than 75 kW that were manufactured by Case IH, Claas, Fendt, John Deere, Massey Ferguson, and New Holland and were advertised on https://www.agriaffaires.com/ (accessed on 15 July 2022), https://www.mascus.com/ (accessed on 15 July 2022), and https://www.tractorpool.com/ (accessed on 15 July 2022) by professional retailers (for which the machine is in good condition as the retailer is obliged to provide a legal warranty on the product, and the price realization expectations are delimited by the financial requirements related to their business sustainability) in Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Italy, Latvia, Lithuania, Netherlands, Norway, Poland, Spain, Sweden, and the United Kingdom [37] by professional sellers. The listings needed to feature the working hours, year of manufacture, and price (VAT excluded and price converted into Euros). At least 300 working hours were required, as tractors with less hours advertised from professionals come from demonstration programs or rental programs; hence, there is an outside source of income in which the seller alters the price realization expectations.

The tractor models were aligned with the OEM's official nomenclature (as sellers tend to include features in the product name with the intent of differentiating their offering), and redundant advertisements were eliminated (as it is frequent that the sellers have business systems interfaced with the different websites in order to achieve the largest possible product awareness; thus, more than one website can feature the same offering).

The dataset obtained for this study was composed of 10,303 uniquely categorized, advertised tractor observations (Table 3 and Figure 3)

Table 3. Dataset size grouped by country and power segment.

Country	(<100 kW)	(100–120 kW)	(120–160 kW)	(>160 kW)	Total
Austria	77	28	19	32	156
Belgium	12	24	59	52	147
Denmark	105	92	126	183	506
Estonia	7	9	20	38	74
Finland	117	83	58	15	273
France	1097	773	992	444	3306
Germany	459	420	838	1132	2849
Italy	65	35	39	66	205
Latvia	7	6	7	22	42
Lithuania	34	24	25	85	168
Netherlands	117	68	105	54	344
Norway	93	39	37	4	173
Poland	134	114	115	138	501
Spain	60	43	48	22	173
Sweden	246	116	119	70	551
United Kingdom	192	246	273	124	835
Total	2822	2120	2880	2481	10,303

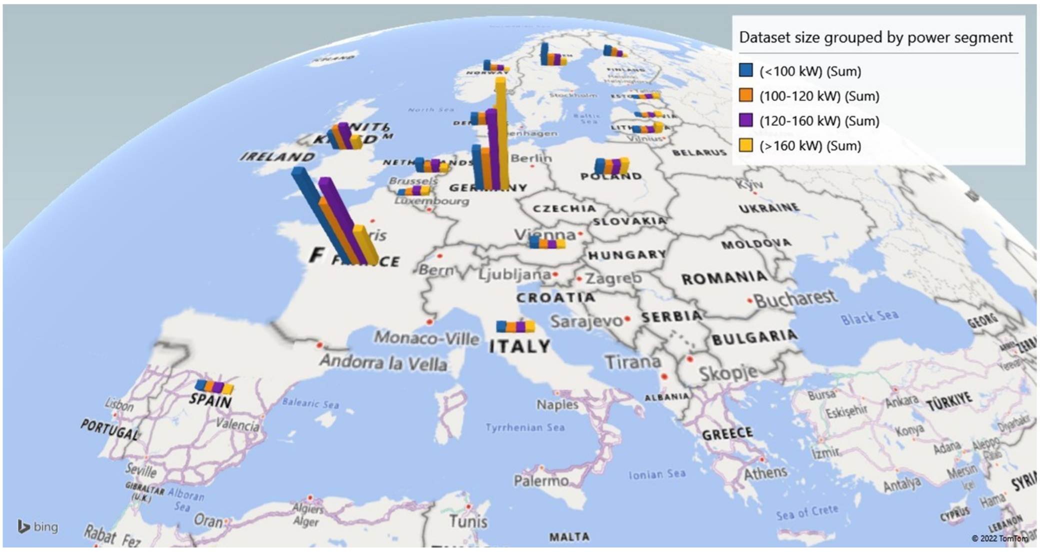

Figure 3. Dataset size grouped by country and power segment.

2.2. Data Systematization and Preprocessing

Calculating the residual value (*RV*) as:

$$RV = \frac{Used\ tractor\ retail\ price\ (€)}{Used\ tractor\ retail\ price\ when\ new\ (€)} \tag{1}$$

presents quite a challenge. As mentioned above, the availability of used tractor transactional information is scarce, and obtaining the tractor retail prices from all 16 countries in the scope of this study since 1998 is quite an endeavor. Hence, a novel approach was taken by means of the new equivalent tractor concept:

$$RV = \frac{Used\ tractor\ retail\ price\ (€)}{Equivalent\ new\ tractor\ (€)} \tag{2}$$

2.2.1. New Equivalent Tractor

A tractor model belongs to a tractor series, with which it shares a wheelbase, mass, and most characteristics, with the key differentiator being its power. As technology evolves, the tractor series are replaced by newer series with enhancements that improve efficacy and/or efficiency. The evolution is such that it is sometimes not possible to find a current replacement model with the same features as a used one, as those features were rendered obsolete (e.g., synchronized transmissions, two-wheel drive, unsuspended front axle, open circuit hydraulic system, or an open operator station). The retail price of the new series' models includes any inflation changes as well as any cost derived from regulations compliance and any additional features deemed necessary by the market (Table 4).

Obtaining the retail price of current models will be much easier for the subject matter experts using the method described in this model, as the prices are available through some manufacturer's websites and/or through a dealer's quote.

Table 4. Model evolution example.

Model	Year	Power	Wheelbase	Minimum Mass	Transmission Options
Current Model	2022–2020	186 kW	2925 mm	11,400 kg	Infinitely variable transmission, 23-speed full powershift
Predecessor-1	2020–2014	186 kW	2925 mm	10,470 kg	Infinitely variable transmission, 23-speed full powershift
Predecessor-2	2014–2012	172 kW	2925 mm	10,285 kg	Infinitely variable transmission, 23-speed full powershift
Predecessor-3	2012–2006	173 kW	2860 mm	7900 kg	Infinitely variable transmission, 19-speed full powershift, 20-speed partial powershift, 16-speed partial powershift,
Predecessor-4	2006–2003	141 kW	2860 mm	7772 kg	Infinitely variable transmission, 19-speed full powershift, 20-speed partial powershift
Predecessor-5	2003–1996	130 kW	2800 mm	6510 kg	Infinitely variable transmission, 19-speed full powershift, 20-speed partial powershift
Predecessor-6	1996–1992	127 kW	2800 mm	6495 kg	19-speed full powershift, 16-speed partial powershift
Predecessor-7	1992–1988	117 kW	2670 mm	6400 kg	15-speed full powershift, 16-speed partial powershift
Predecessor-8	1998–1983	117 kW	2670 mm	5790 kg	15-speed full powershift, 16-speed partial powershift
Predecessor-9	1982–1978	107 kW	2710 mm *	5300 kg	8-speed full powershift, 16-speed partial powershift
Predecessor-10	1978–1973	102 kW	2700 mm *	4415 kg	8-speed full powershift, 16-speed partial powershift, 8-speed partially synchro
Predecessor-11	1972–1971	95 kW	2700 mm *	4105 kg	8-speed full powershift, 8-speed partially synchro

* Two-wheel drive (2 WD).

2.2.2. Tractor Family

Manufacturers group their similar models in series. In some cases, these series are quite large and can include several wheelbases, whereas other series are split into separated series (e.g., Case IH's Puma Series vs. New Holland's T7 SWB, and T7 LWB or John Deere's 6 R series, which features models ranging from 6500 kg to 9650 kg of shipping mass). Others differentiate their series by the featured transmission (e.g., Case IH's CVX, Claas' CMATIC, Massey Ferguson's Dyna-VT, and New Holland's Auto Command series, which features a continuous variable transmission vs. the stepped transmissions featured by equivalent models; Massey Ferguson and New Holland go a step further and differentiate between their models by featuring partial powershift transmissions such as the Dyna-4 and Dyna-6, Electro Command, and Dynamic Command). Other manufacturers use their model nomenclature to differentiate the specifications level (e.g., John Deere's premium R series vs. the no so premium M series).

In addition, not all series have the same number of sales; thus, the adverts available on the internet are also quite different, allowing for the series to split into different families that share common features and specifications (Table 5).

Table 5. Family model details.

Brand Id *	Family Id *	Number of Models	Min Power (kW)	Max Power (kW)	Wheelbase (mm)	Minimum Mass (kg)	Maximum Mass (kg)
A	A∣Ba	5	184	279	3155	11,290	18,000
	A∣Bb	5	184	250	3155	11,290	18,000
	A∣Ca	3	184	221	2995	10,500	16,000
	A∣Ea	7	110	177	2884	6782	13,000
	A∣Eb	5	110	162	2884	6782	13,000
	A∣Ga	4	92	107	2679	5300	9500
	A∣Gb	5	85	107	2454	5190	9000
	A∣Ib	3	73	84	2420	4390	8000
	A∣Jb	7	43	84	2235	2880	6000
B	B∣Ba	4	232	298	3150	12,840	18,000
	B∣Ca	7	142	195	2980	8300	14,000
	B∣Cb	7	142	195	2980	8300	14,000
	B∣Ea	4	110	129	2820	6570	12,000
	B∣Eb	4	110	129	2820	6570	12,000
	B∣Ga	3	103	116	2564	5800	11,000
	B∣Gb	3	103	116	2564	5800	11,000
	B∣Hb	6	63	99	2525	4700	8500
C	C∣Aa	4	291	380	3300	14,000	18,000
	C∣Ba	5	202	291	3050	10,830	18,000
	C∣Ca	4	166	211	2950	9370	16,000
	C∣Da	6	106	176	2783	7735	14,000
	C∣Ga	4	91	120	2560	6050	10,500
	C∣Ha	4	74	97	2420	4810	8500
D	D∣B0	7	180	294	3050	13,528	18,000
	D∣C0	6	154.5	228	2925	10,470	16,000
	D∣E0	3	129	158	2183	8300	13,450
	D∣E1	2	126	143	2800	7015	12,300
	D∣F0	3	99	114	2765	6400	11,750
	D∣F1	3	107	114	2765	6700	11,000
	D∣G0	3	81	96	2580	6000	9950
	D∣G1	3	96	103	2580	5800	10,450
	D∣H1	6	66	88	2400	5750	10,450
	D∣I0	4	66.6	91.9	2250	4300	8600
	D∣I1	4	55	85	2300	3600	6000
E	E∣Ba	5	176	250	3093	10,800	18,000
	E∣Ea	8	106	173	3000	5800	13,000
	E∣Eb	9	101	176	3000	5800	13,000
	E∣Ec	2	101	106	2880	5800	12,500
	E∣Ga	6	88	129	2870	5500	11,500
	E∣Gb	6	88	129	2670	5500	11,500
	E∣Gc	4	88	110	2670	5500	8800
	E∣Hb	3	82	97	2550	4800	8421
	E∣Hc	5	70	97	2550	4800	8421
F	F∣Ba	5	184	279	3500	11,235	18,000
	F∣Bb	5	184	279	3500	11,235	18,000
	F∣Ca	3	184	221	2995	10,500	16,000
	F∣Ea	4	132	177	2884	8140	13,000
	F∣Eb	4	132	177	2884	8140	13,000
	F∣Fa	4	103	132	2789	6650	11,500
	F∣Fb	4	103	132	2789	6650	11,500
	F∣Ga	4	85	107	2684	6360	10,500
	F∣Gb	6	85	107	2684	6110	10,500
	F∣Ib	3	74	86	2380	5300	8000
	F∣Jb	5	55	84	2285	3700	6500

* Brand, family and model are anonymized to avoid any bias.

The combination of the new equivalent tractor and the tractor family have been paramount contributors to coalesce a dataset for this study, which is composed of 10,303 tractors.

2.3. Data Analysis

As previously stated, one of the goals of this study is to provide an easy-to-use method for residual value stakeholders. With 1.1 billion users (one in eight people on the planet), Microsoft Excel is one of the most ubiquitous software in both professional and domestic environments. Hence, considering Microsoft Excel as the first option was clear.

Microsoft Excel offers functions that allow several models to make multiple variable regressions, enabling the evaluation of the following regressions:

$$\text{Linear (lin-lin)}: \quad RV = Coef_A + Coef_B \cdot Hours + Coef_C \cdot Age \tag{3}$$

$$\text{Logarithmic (lin-log)}: \quad RV = Coef_A + Coef_B \cdot ln(Hours) + Coef_C \cdot ln(Age) \tag{4}$$

$$\text{Power (log-log)}: \quad RV = Coef_A \cdot Coef_B^{Hours} \cdot Coef_C^{Age} \tag{5}$$

$$\text{Exponential (log-lin)}: \quad RV = Coef_A \cdot e^{Coef_B \cdot Hours} \cdot e^{Coef_C \cdot Age} \tag{6}$$

In order to evaluate alternative regression options, several different models were analyzed with Matlab, including parametric and non-parametric models (Table 6).

Table 6. Tested fitted regression models.

Model Type	Subtype
Ensemble	Bagged Trees Boosted Trees
Gaussian Process Regression (GPR)	Exponential GPR Matern 5/2 GPR Rational Quadratic GPR Squared Exponential GPR
Kernel	Least Squares Regression Kernel SVM Kernel
Linear Regression	Linear Robust Linear
Neural Network	Bi-layered Neural Network Medium Neural Network Narrow Neural Network Tri-layered Neural Network Wide Neural Network
Supported Vector Machine (SVM)	Coarse Gaussian SVM Cubic SVM Fine Gaussian SVM Linear SVM Medium Gaussian SVM Quadratic SVM
Tree	Coarse Tree Fine Tree Medium Tree

The regression trees, support vector machines, ensembles of regression trees, Gaussian process regressions, and neural networks were optimized by machine learning.

In the interest of examining the predictive accuracy of the fitted models, regressions were made with 3, 5, 7, and 9 predicting variables and with a 3-, 5-, 7-, and 9-fold cross-over validation. In addition, 5%, 10%, 15%, 20%, and 25% hold-out validation models were used (in one instance, one regression was performed with a 5% training dataset) (Table 7).

Table 7. Number of predicting variables and validations evaluated.

Predictor Variables	Validation									
	Cross-Over				Hold-Out					
	3 Folds	5 Folds	7 Folds	9 Folds	5%	10%	10% (T5%)	15%	20%	25%
3		+								
5		+								
7	+	+	+	+	+	+	+	+	+	+
9		+								

In regression analysis, the root mean squared error (RMSE) and adjusted R^2 (RSqAdj) metrics were used to evaluate the performance of the different models.

The root of the error was used to obtain an error with the same unit as the outcome variable for easier interpretation purposes. The closer the point is to the regression, the lower the metric value is and the higher the accuracy of the regression model is. When a model is 100% perfect, this metric value will be equal to zero.

The adjusted R^2 is a better evaluation metric than R^2. The R^2 is a statistical measure that represents the proportion of variation in the dependent variable that is explained by the regression model. The adjusted R^2 considers the number of predictor variables used to predict the dependent variable [38].

As the proposed power regression model is based on tractor families and uses two predictors, the same Matlab regression models seen in Table 6 including regression trees, support vector machines, ensembles of regression trees, Gaussian process regressions, and neural networks optimized by machine learning) were analyzed for the tractor families that obtained the best RMSE results with the proposed power regression model.

3. Results

3.1. Proposed Regression Models

The proposed power regression model (5) offered the best RMSE and R^2 adjusted results (Table 8 and Figure 4).

Figure 4. Power regression results (bubble size represents number of observations).

Table 8. Tractor family power regression results.

Brand Identifier	Family Identifier	RMSE	RSqAdj	Observations
A	A | Ba	0.0031	0.9773	20
	A | Bb	0.0154	0.9804	80
	A | Ea	0.0279	0.9657	216
	A | Eb	0.1039	0.9664	212
	A | Gb	0.0068	0.9713	225
	A | Ib	0.1989	0.9381	66
B	B | Cb	0.2647	0.9487	394
	B | Eb	0.3786	0.9479	536
	B | Gb	0.0856	0.8549	64
	B | Hb	0.3879	0.9202	215
C	C | Ba	0.4028	0.9642	388
	C | Ca	0.3890	0.9608	266
	C | Da	0.8513	0.9713	502
	C | Ga	0.1674	0.9497	160
	C | Ha	0.0842	0.9446	36
D	D | B0	0.2124	0.9742	291
	D | C0	0.1868	0.9753	613
	D | E0	0.3358	0.9579	727
	D | F0	0.7231	0.9594	907
	D | F1	0.2544	0.8969	162
	D | G0	0.7570	0.9311	466
	D | G1	0.5214	0.8146	306
	D | H1	0.6589	0.9061	93
	D | I0	0.1239	0.9301	83
	D | I1	0.2733	0.3018	51
E	E | Ba	0.2578	0.9763	88
	E | Ea	0.0796	0.9629	262
	E | Eb	0.1099	0.9697	338
	E | Ga	0.0189	0.9626	36
	E | Gb	0.6431	0.9258	495
	E | Gc	0.0849	0.9783	36
	E | Hb	0.3440	0.9543	73
	E | Hc	0.1498	0.9250	86
	E | Ib	0.0173	0.9492	55
F	F | Ba	0.1160	0.9738	113
	F | Bb	0.0890	0.9502	53
	F | Ea	0.0215	0.9522	70
	F | Eb	0.1030	0.9785	299
	F | Fa	0.0287	0.9434	66
	F | Fb	0.0182	0.9695	386
	F | Gb	0.0227	0.9505	410
	F | Ib	0.0196	0.9561	247
	F | Jb	0.0239	0.8509	28

3.2. Fitted Regression Models with Multiple Variables and Validations

Even if one of the goals of this study is to provide the best possible results with the most accessible tools and methodology, it is indispensable to evaluate more advanced models and tools. Therefore, as previously stated, multiple models were evaluated (Table 6) using different variables and validation methods (Table 7).

Models with seven predictors showed better RMSE values when compared to 3, 5, and predictor-tested models. Models with hold-out validation demonstrated better RMSE values than those with cross-out validation. The best overall model was the rational quadratic Gaussian process regression with seven predicting variables, which was validated with a 10% hold-out and an RMSE value of 0.046 (Table 9).

Table 9. Fitted regression models with multiple variables and validation RMSE results.

<table>
<tr><th>Model Type</th><th>Subtype</th><th>Analysis</th><th>Minimum RMSE</th><th>RSq Adj</th></tr>
<tr><td rowspan="2">Ensemble</td><td>Boosted Trees</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0783</td><td>0.8664</td></tr>
<tr><td>Bagged Trees</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0697</td><td>0.8940</td></tr>
<tr><td rowspan="4">Gaussian Process Regression (GPR)</td><td>Exponential GPR</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0638</td><td>0.9096</td></tr>
<tr><td>Squared Exponential GPR</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0650</td><td>0.9060</td></tr>
<tr><td>Matern 5/2 GPR</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0648</td><td>0.9068</td></tr>
<tr><td>Rational Quadratic GPR</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0646</td><td>0.9074</td></tr>
<tr><td rowspan="2">Kernel</td><td>SVM Kernel</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.1031</td><td>0.7639</td></tr>
<tr><td>Least Squares Regression Kernel</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.1108</td><td>0.7274</td></tr>
<tr><td rowspan="3">Linear regression</td><td>Linear</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0769</td><td>0.8710</td></tr>
<tr><td>Robust Linear</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0772</td><td>0.8702</td></tr>
<tr><td>Interactions Linear</td><td>Five predictors, cross-over 5-fold (C|5/5)</td><td>0.0839</td><td>0.8545</td></tr>
<tr><td rowspan="5">Neural Network</td><td>Narrow Neural Network</td><td>Seven predictors, hold-out 15% (H|7/0.10)</td><td>0.0716</td><td>0.8936</td></tr>
<tr><td>Medium Neural Network</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0741</td><td>0.8779</td></tr>
<tr><td>Wide Neural Network</td><td>Five predictors, cross-over 5-fold (C|5/5)</td><td>0.0816</td><td>0.8626</td></tr>
<tr><td>Bi-layered Neural Network</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0702</td><td>0.8906</td></tr>
<tr><td>Tri-layered Neural Network</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0715</td><td>0.8864</td></tr>
<tr><td>Stepwise Linear Regression</td><td>Stepwise Linear</td><td>Five predictors, cross-over 5-fold (C|5/5)</td><td>0.0839</td><td>0.8545</td></tr>
<tr><td rowspan="6">Support Vector Machines (SVM)</td><td>Linear SVM</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0775</td><td>0.8690</td></tr>
<tr><td>Quadratic SVM</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0662</td><td>0.9025</td></tr>
<tr><td>Cubic SVM</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0684</td><td>0.8959</td></tr>
<tr><td>Fine Gaussian SVM</td><td>Three predictors, cross-over 5-fold (C|5/5)</td><td>0.0978</td><td>0.8028</td></tr>
<tr><td>Medium Gaussian SVM</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0650</td><td>0.9060</td></tr>
<tr><td>Coarse Gaussian SVM</td><td>Seven predictors, hold-out 10% (H|7/0.10)</td><td>0.0721</td><td>0.8844</td></tr>
<tr><td rowspan="3">Tree</td><td>Fine Tree</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0845</td><td>0.8444</td></tr>
<tr><td>Medium Tree</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0812</td><td>0.8564</td></tr>
<tr><td>Coarse Tree</td><td>Seven predictors, hold-out 5% (H|7/0.05)</td><td>0.0821</td><td>0.8530</td></tr>
</table>

This model would rank thirteenth when compared with the tractor families with the best RMSEs of the proposed power model (Table 8).

The exponential Gaussian process regression (GPR) demonstrated more consistent RMSE results across all the tested variables and validations (Figure 5).

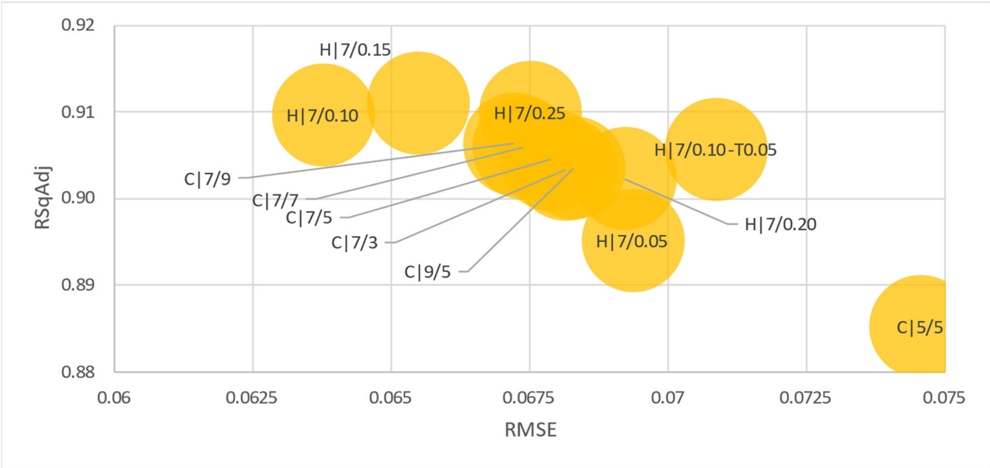

Figure 5. Exponential Gaussian process (GPR) results' RMSE for different tested variables and validations (bubble size represents number of observations).

3.3. Fitted Regression Models of Tractor Families

As the proposed methodology on power regression models is based on two predicting variables of tractor families, it was essential to test more advanced software using more advanced models.

Hence, the tractor families that rendered the best power regression model RMSE value results (Figure 4) were tested using the same fitted models and a 10% hold-out validation to provide data sets (Table 6).

The optimized Gaussian process regressions of the two predictors, validated with a 10% hold-out of the considered tractor families, provided very satisfactory RMSE and RSqAdj results (Table 10).

Table 10. RMSE values of the results of two predictors, grouped by families evaluated.

Tractor Family	Model Type Preset	RMSE	RSqAdj	Observations
A I Bb	Optimized Gaussian Process Regression	0.0546	0.9012	78
A I Ea	Optimized Gaussian Process Regression	0.0697	0.8157	215
A I Gb	Optimized Gaussian Process Regression	0.0735	0.8191	224
E I Ea	Exponential GPR	0.0700	0.8334	259
E I Ib	Interactions Linear	0.0780	0.3124	52
F I Ea	Linear	0.0764	0.7246	66
F I Fa	Optimized Gaussian Process Regression	0.0639	0.6549	64
F I Fb	Exponential GPR	0.0628	0.8868	378
F I Gb	Optimized Gaussian Process Regression	0.0880	0.7505	409
F I Ib	Optimized Gaussian Process Regression	0.0803	0.8025	244

Across most family groups, the best overall model was the optimized Gaussian process regression (OGPR) model (Figure 6).

The results of the proposed power regression model of two predictors, grouped by families tested, were better than the most accurate regression performed by Matlab, even if Matlab was optimized by machine learning (Table 11 and Figure 7).

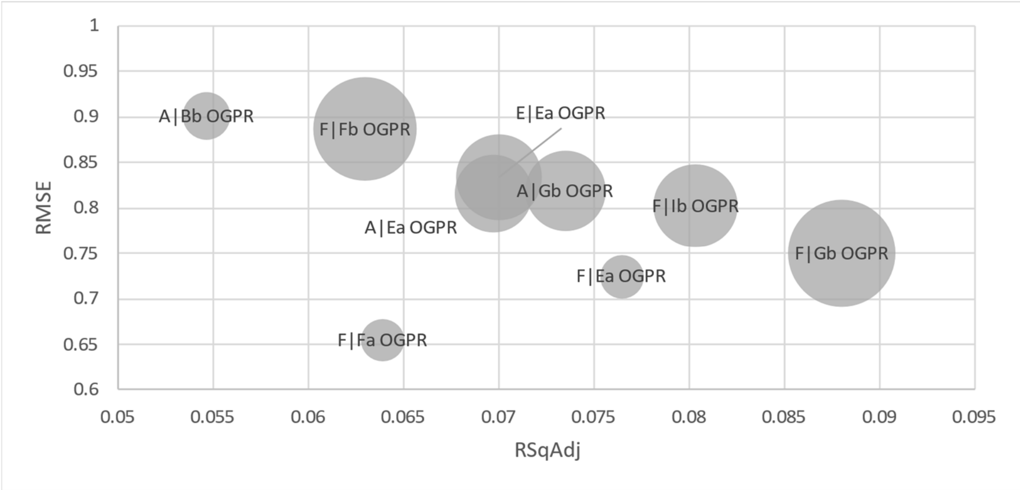

Figure 6. RMSE values for optimized Gaussian process results of two predictors, grouped by families tested (bubble size represents number of observations).

Table 11. Regression results for tractor families using two predictors.

Tractor Family	Power Linear Regression		Optimized Gaussian Process Regression (GPR)		Observations
	RMSE	RSqAdj	RMSE	RSqAdj	
A | Bb	0.0154	0.9804	0.0546	0.9012	80
F | Fb	0.0182	0.9695	0.0629	0.8863	386
F | Fa	0.0287	0.9434	0.0639	0.6549	66
A | Ea	0.0279	0.9657	0.0697	0.8157	216
E | Ea	0.0796	0.9629	0.0700	0.8333	262
A | Gb	0.0068	0.9713	0.0735	0.8191	225
F | Ea	0.0215	0.9522	0.0764	0.7246	70
E | Ib	0.0173	0.9492	0.0796	0.2832	55
F | Ib	0.0196	0.9561	0.0803	0.8025	247
F | Gb	0.0227	0.9505	0.0880	0.7505	410

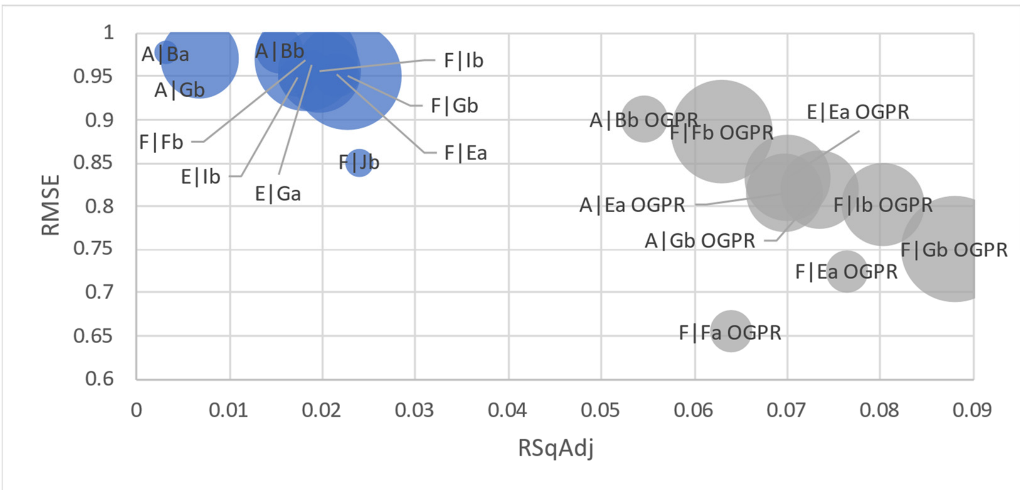

Figure 7. Two predictors, grouped by family power regression (blues) and OGPR (grey) results (bubble size represents number of observations).

The proposed power regression model seems to follow the different tractor family residual-value behaviors quite precisely. The fact that the second-best tested model was exponential regression, as was found by Witte, Back, Sponagel, and Bahrs [26], proves that these models exhibit better performance than more complex models such as optimized Gaussian regressions (OGPR).

4. Discussion

The robustness of the proposed power regression model was compared to the following models:

1. Models referenced by previous studies, which offered sufficient detail to process the dataset (Table 1);
2. Fitted regression models of the complete data set with multiple variables and validations (Tables 6 and 7);
3. Fitted regression models of tractor families with the same predictors used in the proposed power linear regression (Figure 4).

4.1. Models Referenced by Previous Studies

The complete data set was processed using data from previous studies whenever it was possible (when enough details were provided) (Table 12 and Figure 8).

Table 12. Results of previous studies.

Author	RMSE	RSqAdj	Observations
Cross, T. L., and Perry, G. M. (1995).	12.4901	0.7573	9630
Unterschultz, J., and Mumey, G. (1996).	11.7518	0.4234	5417
Cross, T. L., and Perry, G. M. (1996).	1.0615	0.4634	9630
Wu, J., and Perry, G. M. (2004).	6.8064	0.7389	9630
Fenollosa, M. L., and Guadalajara, N. (2007).	7.2109	0.5272	6768
Wilson, P., and Tolley, C. (2004).	18.2890	0.7628	9630
Wilson, P. (2010). OLS	9.9710	0.7736	9630
Wilson, P. (2010). Box–Cox	42.7132	0.7326	9630
ASABE. (2011 (R2020)).	21.8687	0.7435	9630
Kay, R., Edwards, W., and Duffy, P. (2020).	14.2284	0.6508	8157
Witte, F., Back, H., Sponagel, C., and Bahrs, E. (2022)	10.6769	0.5314	8823
Ruiz-Garcia and Sanchez-Guerrero (2022)	9.3372	0.8149	10,253

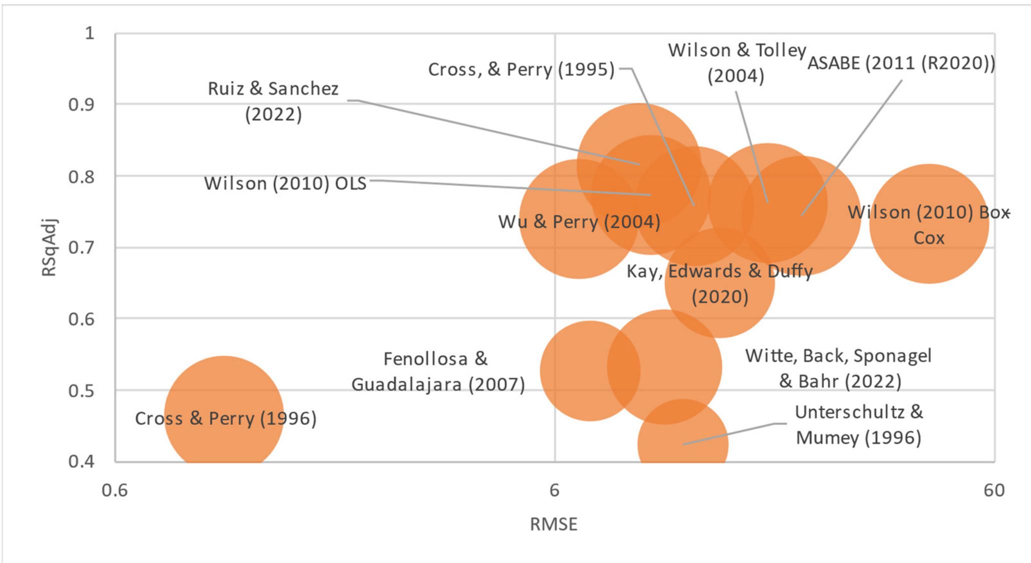

Figure 8. Reults of previously referenced studies (bubble size represents number of observations).

The proposed power regression model (RMSE = 1.5574 | RSqAdj = 0.8457) demonstrated more predictive robustness Table 1**.** shows how previous studies used, in addition to years of age and hours of usage, brand and power in order to predict the residual value behavior. However, Table 2 shows that power is not enough to differentiate residual value behavior, as even similar tractor families from the same brand with the same power can feature different sizes, masses, transmissions, and user interfaces. The proposed model takes these factors into consideration, drilling down to model levels and grouping them in tractor families to lay a better foundation for more robust results.

4.2. General

The proposed power regression model provided the best RMSE and RSqAdj of all the tested models (Figure 9).

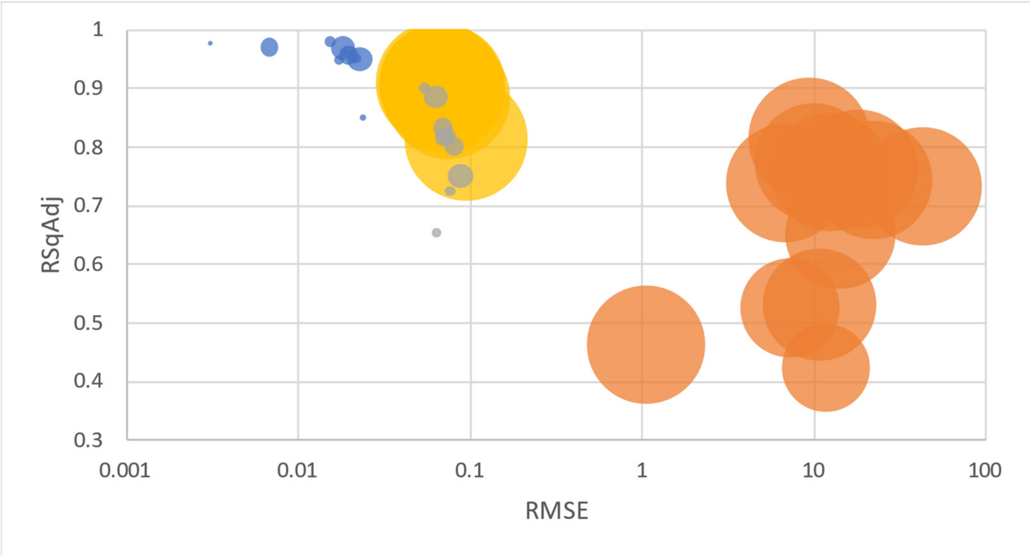

Figure 9. Summary of all regressions considered in this study (proposed power regression in blue, previous studies referenced in orange, fitted multiple variables and validation models in yellow, and fitted tractor family models in gray) (bubble size represents number of observations).

Compared to the previous studies referenced, the proposed power regression model provides better RMSE and RSqAdj values as it considers not only the brand and very similar power and tractor size (wheelbase and mass) but also very similar specification levels (e.g., transmissions and user interfaces), relating these factors to an equivalent new model that provides a precise price reference, including inflation and production costs. These variations yield a better foundation for more robust results.

Compared to more advanced fitting models that require specific software, the proposed power regression model provides better RMSE and RSqAdj values and a simpler methodology that is applicable using a more mainstream software.

The model is fed from public and freely available data. Its ease of use by means of widely known software, united with its transparency, provides infinite analysis options that can be easily visualized (Figure 10).

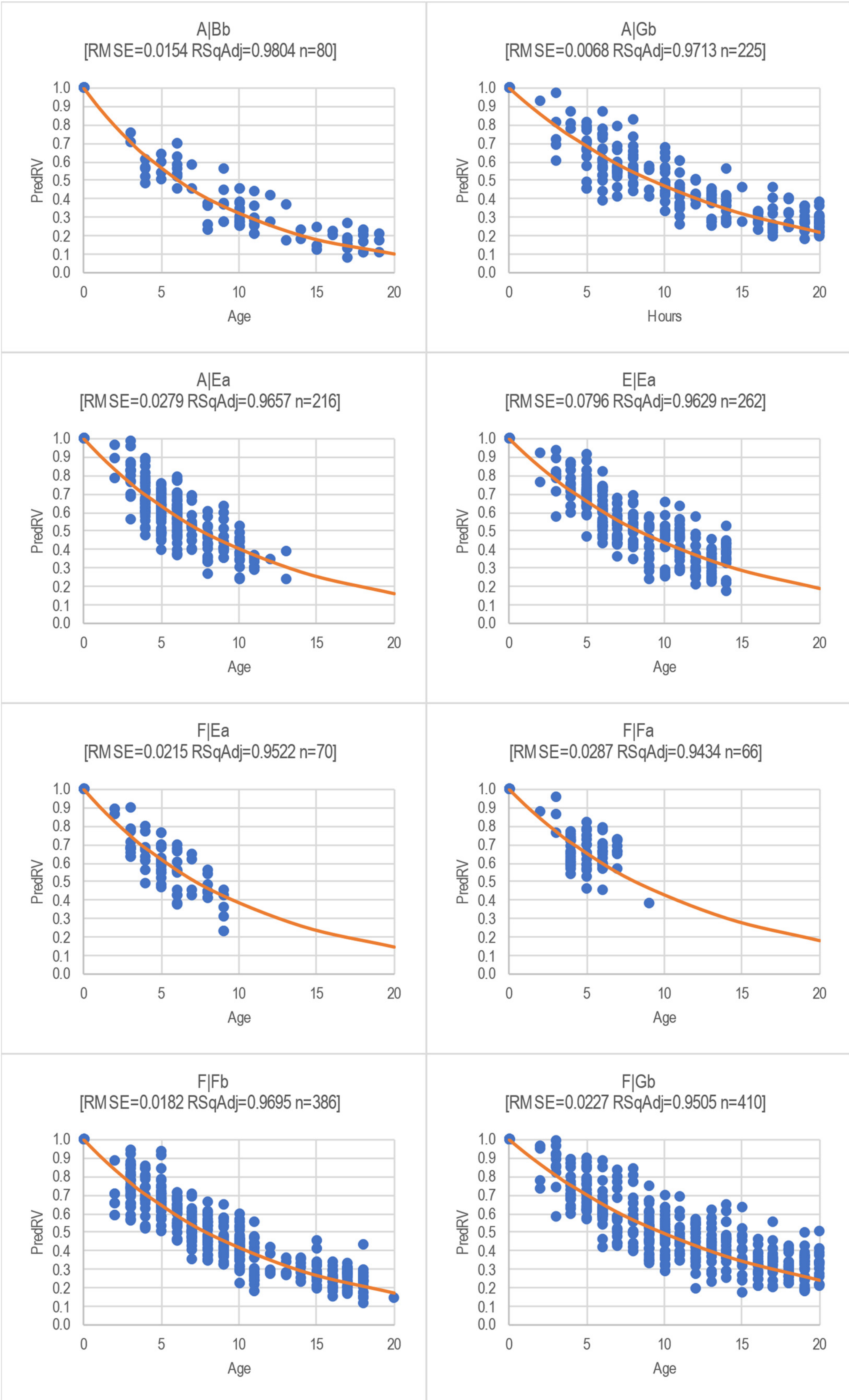

Figure 10. Dataset and power regression for 500 h per year (HPY) results of top eight RMSE tractor families.

The charts created based on the power linear regression model (Figure 10) clearly depict that the more powerful A | Bb tractor family (Table 5) loses value faster than the smaller A|Gb tractor family; both are from the same brand. It also shows how the similar tractor families, A|Ea and E|Ea, and F|Ea, from a different family, which feature similar powers, wheelbases, masses, and stepless transmissions, hold their residual value differently. Additionally, Figure 10 depicts how two very similar tractor families from the same brand, F|Fb and F|Gb, which have a very similar power, wheelbase, mass, and stepped transmission, hold residual value differently.

The methodology and model can be used to compare how the residual value of tractors behaves in tractors with the same power but diverse power densities (kW/kg), transmission options (e.g., continuously variable transmissions, full powershift, and partial powershift transmissions), and user interfaces (from classic to highly advanced).

The methodology can be applied to other types of agricultural machinery, such as combines and self-propelled forage harvesters, as well as to European auction results with similar positive results.

5. Conclusions

This equivalent, new, tractor-based and family-grouped methodology, leading to a power regression curve, solves the issues that affect traditional residual value studies, based on auctions and advertisements, which try to bypass the lack of large transactional datasets. This is true even if the traditional residual value studies take into consideration more predictors (brand, power, economic factors, etc.) than the main drivers (years of age and hours of use) by means of more advanced models (linear, exponential, ordinary least squares, Box–Cox, and robust linear), as can be observed in this study. Simultaneously, the new methodology provides a robust RMSE = 1.5574 and RSqAdj = 0.8457, values which are unsurpassed by all the previous studies and models tested.

The proposed power regression model considers each tractor model on its own. Therefore, there are no interferences from other tractor models with same power but a totally different specification level, wheelbase, and weight.

The proposed power regression model considers the price increase due to emission regulations as well as specification evolution, comparing the used tractor retail price relative to the equivalent new tractor retail price.

The proposed power regression model compensates for the small statistical population by grouping the models in family groups instead of tractor series in cases for which a small statistical population is found, or by subdividing the tractor series when there are sufficient statistical data points and significant differences within tractor series that feature a large number of models.

Despite the simplicity of the proposed power regression model, it was not surpassed by more advanced models (including machine learning optimization) performed by more specialized software.

The proposed power regression model requires a simple internet search for used equipment websites and just two inquiries to sellers (one for the new, equivalent tractor retail price and another inquiry for the used tractor retail price). In other words, it is easy to obtain information that is later transparently processed using a universally known software.

It would be of great interest to identify a way to increase the size of the dataset by including auction results as a source of transactional information if a correlation between retail and wholesale prices is found.

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