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A Comparison of Artificial Neural Network and Time Series Models for Timber Price Forecasting

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Abstract: The majority of the existing studies on timber price forecasting are based on ARIMA/SARIMA autoregressive moving average models, while vector autoregressive (VAR) and exponential smoothing (ETS) models have been employed less often. To date, timber prices in primary timber markets have not been forecasted with ANN methodology. This methodology was used only for forecasting lumber futures. Low-labor-intensive and relatively simple solutions that can be used in practice as a tool supporting decisions of timber market participants were sought. The present work sets out to compare RBF and MLP artificial neural networks with the Prophet procedure and with classical models (i.e., ARIMA, ETS, BATS, and TBATS) in terms of their suitability for forecasting timber prices in Poland. The study material consisted of quarterly time series of net nominal prices of roundwood (W0) for the years 2005–2021. MLP was found to be far superior to other models in terms of forecasting price changes and levels. ANN models exhibited a better fit to minimum and maximum values as compared to the classical models, which had a tendency to smooth price trends and produce forecasts biased toward average values. The Prophet procedure led to the lowest quality of projections. Ex-post error-based measures of prediction accuracy revealed a complex picture. The best forecasts for alder wood were obtained using the ETS model (with RMSE and MAE values of approx. 0.38 € m^{-3}). ETS also performed well with respect to beech timber, although in this case BATS was just as good in terms of RMSE, while the difference between ETS and neural models amounted to as little as 0.64 € m^{-3}. Birch timber prices were most accurately predicted with BATS and TBATS models (MAE 0.86 € m^{-3}, RMSE 1.04 € m^{-3}). The prices of the most popular roundwood types in Poland, i.e., Scots pine, Norway spruce, and oaks, were best forecasted using ANNs, and especially MLP models. Among the neural models for oak (MAE 4.74 € m^{-3}, RMSE 8.09 € m^{-3}), pine (MAE 2.21 € m^{-3}, RMSE 2.83 € m^{-3}), beech (MAE 2.31 € m^{-3}, RMSE 2.70 € m^{-3}), alder (MAE 1.88 € m^{-3}, RMSE 2.40 € m^{-3}), and spruce (MAE 2.44 € m^{-3}, RMSE 2.58 € m^{-3}), the MLP model was the best (the RBF model for birch). Of the seven models used to forecast the prices of six types of wood, the worst results were obtained for oak wood, while the best results were obtained for alder.

Keywords: primary timber market; price prediction; artificial neural networks; classical models

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1. Introduction

The global timber industry is becoming increasingly complex, interconnected, and intersectoral. It is affected to an ever greater extent by climate and energy policies, advances in the area of nanofibers and biochemical technologies, the growing role of forestry services, and changes in forest use [1]. Among the three factors influencing returns on forests (biological growth, timber prices, and land prices), timber prices remain the least predictable. They have an impact not only on periodic dividends from timber sales, but also on timber production strategies [2]. As a result, timber prices are among the most important variables for strategic management in forestry. Thus, timber price forecasting is gaining popularity as an important tool for making informed business decisions.

Price forecasting constitutes a challenge as prices are affected by market variables associated with suppliers and buyers, as well as with substitutability considerations and spatial factors [3]. For a long time now, perfect competition has been taken to be the golden standard for evaluating the ability of the market to perform efficiently. The timber market is formed by all the relationships within the industry, that is, the forestry and timber sectors [4]. Timber prices in the Polish markets depend on the specific features of the timber market, forest ownership structure, the number of processing plants, their capacity, degree of timber processing, as well as timber sale policy and organization. Timber prices are affected not only by supply, but also demand, which depends on the national and international economic situation. Globalization has given rise to interconnections between markets and ever faster responses to macroeconomic changes [5–7]. Under conditions of globalization, timber prices in national markets are more often affected by those in other markets, and especially those in the neighboring countries. This leads to long-term relationships between timber prices in interconnected markets [8–10].

Snowberg et al. [11] showed that prediction markets generally exhibit lower statistical errors than professional forecasters, experts, and polls, and may be used both for discovering and testing economic models. Due to the fast-paced changes in the world's economy, short- and medium-term forecasting is becoming increasingly important, with price forecasts providing a source of knowledge for market actors. Price forecasting constitutes a major tool in decision-making about timber harvesting by forest owners and managers as well as by parties involved in forest sale transactions [5,12]. Knowledge about future timber prices is sought by timber buyers and industrial timber producers, although any forecasts in this respect should be interpreted cautiously, just as it is the case with other predictions [13,14]. Many authors have tried to predict future timber prices based on various methodological approaches [15–23]. For instance, Linden and Uusivuori [24] attempted to predict price movements based on a questionnaire survey on expected timber prices conducted among Finnish forest owners; in their case, forest owners with access to forest management information formed overly optimistic timber price forecasts. In turn, Mo Zhou and Buongiorno [18] proposed a space–time model for forecasting pine wood prices in the south of the United States. According to Bolkesjø [25], a substantial proportion of studies is based on demand and supply models in different geographical areas.

Malaty et al. [5] discussed (structural) changes in stochastic seasonality and time series trends, and their role in forecasting market prices. One difficulty with using data from past time series for predicting future timber price movements is the likelihood of changes in the markets and in society at large [26]. Due to the pressure of numerous factors on timber prices, forecasting in a longer time horizon (several years) usually leads to errors [9]. Despite this, forecasting timber prices from data series has a long history and is important in managing forest resources. The advantages of time series as a base for short-term forecasts are described in [27,28].

There are several ways of approaching the problem of time series forecasting. The most popular methods are based on autoregression involving decision trees or neural networks [29]. A number of studies from around the world have described timber price forecasting in the primary timber market as well as in the wood product market. Most authors have used autoregressive integrated moving averages (ARIMA) [13,14]. Box and Jenkins's (1976) pioneering work on ARIMA models constitutes a milestone in time series analysis. ARIMA is a statistical method involving, among others, exponential smoothing, and has been widely used in analyzing and predicting a variety of phenomena [30]. ARIMA models are relatively more robust and efficient in short-term forecasting than the more complex structural models [31]. ARIMA is based on past data from the time series as well as on past prediction error conditions [32]. Time series with a seasonal component may be forecasted using seasonal ARIMA (SARIMA) models [33,34]. In Poland, time series analysis in the context of timber price forecasting has been investigated by Banaś and Kożuch [35] and Adamowicz and Górna [36], who mostly examined ARIMA and SARIMA models, also with exogeneous variables (SARIMAX).

Other authors have forecasted timber prices using vector autoregression (VAR) models in conjunction with structural time series models (STSMs) [2,5,15,19]. Khajurii et al. analyzed timber harvesting options for spruce stands in north-eastern Ontario [37], with timber prices modeled as a mean reverting process involving a state–space filter (reversion concerned the slope as well as continuous and stochastic time shifts). Kongas and Baudin [38] developed a methodology for forecasting forest product demand, supply, and sales in the European forestry sector up to 2020 with estimated elasticities. In turn, Buongiorno [6] used the global forest products model (GFPM) to predict timber prices and production.

A plethora of models can be used for forecasting economic phenomena and the prices of natural resources. Both exponential smoothing (ETS) and artificial neural networks (ANNs) can be used in linear and nonlinear modeling. ETS models consist of error, trend, and seasonality components [39]. Linear ETS is a special case of ARIMA, while nonlinear ETS models do not have ARIMA counterparts. Linear and nonlinear ETS help capture linear and nonlinear patterns, respectively. ARIMA models may ensure a better fit only when the analyzed stationary time series is truly Gaussian. Consequently, if a time series does not meet any of the ARIMA conditions, a hybrid model needs to be used, or ARIMA may be replaced with ETS due to the latter's linear/nonlinear versatility [40]. In turn, the TBATS method involving trigonometric exponential smoothing incorporates seasonal components with periodic integers and non-integers, both dual and single or semi-seasonal. Fajar and Nonalisa [41], who used TBATS to predict chili prices, showed that it is superior to BATS in a short-term prediction horizon, mostly due to the fact that the former requires fewer numerical parameters for estimation. Finally, Dehghani and Bogdanovic [42] applied a BATS algorithm for predicting copper prices.

The Prophet forecasting model, developed by Facebook, can be used for time series exhibiting both trends and seasonality effects. Prophet was first used in 2017 for time series forecasting based on an additive model. It can be fit into historical data spanning multiple seasons and exhibiting strong seasonal effects, and is fully automatic. This model has been applied, e.g., for predicting the spread of the coronavirus pandemic and forecasting business and price data [43–46].

Currently, the prices of natural resources are increasingly often forecasted using ANNs, which are flexible data-based models approximating a large class of nonlinear problems to a desired level of accuracy. ANNs, which involve soft-computing techniques, are the most accurate technique implemented in forecasting models in a wide array of domains, such as social and economic sciences, engineering, business, finance, and stock exchanges [47]. Deep learning can be defined as a special kind of neural networks composed of multiple layers. These networks are better than traditional neural networks in integrating the information from previous events. A recurrent neural network (RNN) is one such machine that has a combination of networks in loop. LSTMs are good for remembering information for a long time. He et al. [48] proved that the artificial neural network (ANN) model is the most competitive, followed by the recurrent neural network (RNN) in the lumber market. In time series forecasting of natural resource prices, ANN models have been shown to be superior to ARIMA [49], while, for example in the mining industry, Mban et al. [50] showed a higher usefulness of ARIMA compared to ANN.In agriculture, ARIMA and ANN models have been used by many researchers, such as Jadhav et al. [51] and Mahto et al. [52]. Reza et al. [53] found NNAR to be more suitable than ARIMA for forecasting wheat and rice prices. ANN models have been sporadically used for such purposes; for instance, by Koutroumanidis et al. [54] to forecast firewood prices and by Lopes et al. [55] to predict lumber prices.

ANNs, as well as Prophet and BATS models, have not been used to forecast roundwood prices in the primary timber market. Since ANN methodology has not been used for the prediction of timber prices to date, the present authors set out to compare the suitability of such models for this purpose. The nonlinearity of neural networks substantially increases their application capacity. In search of the most appropriate network, we tested two types of ANNs: feedforward multilayer perceptron (MLP) and radial basis function (RBF) networks.

Price time series were used for comparative analysis of classical models (ARIMA, ETS, BATS, TBATS), the Prophet model, as well as RBF and MLP neural networks to identify the most suitable models for forecasting timber prices. The accuracy of predictions obtained using the selected classical models and ANNs was assessed on the basis of historical data. We evaluated medium-term forecasts of roundwood prices for the most important forest tree species in Poland (Scots pine, Norway spruce, oaks, birches, alders) generated by means of the aforementioned methodologies.

2. Materials and Methods

2.1. Characteristics of the Primary Timber Market in Poland

The timber market is an important industry market in Poland, dynamizing many other commodity markets. In terms of timber resources and production (supply), Poland ranks fourth and fifth in Europe, respectively (behind Sweden, Germany, France, and Finland). The growth and harvesting of timber in Poland is increasing, with forecasts showing that by 2030 the area of Polish forests will increase to 9.1 million hectares, and their resources will exceed 2.5 billion m^3. In Poland, forestry has significant socio-economic potential; together with the related timber sector, it creates 3.1% of global output, about 9% of exports, and 4% of imports. In 2020, industries related to wood processing, the paper industry, and the furniture industry accounted for 9.5% of the sold production of the Polish industry (PLN 103.4 billion). Poland is among the world's leading producers of particleboard (4th place) and fiberboard (6th place) and is the third largest exporter of fiberboard.

Under the conditions of globalization, the wood market and prices in Poland are linked to the markets of Europe, especially Central Europe. Using spruce wood as an example, a bidirectional relationship and causality between the Austrian, Czech, and Polish markets were demonstrated.

Given the ownership structure of forests in Poland (80% are state-owned), 76.9% are managed by the State Forests National Forest Holding (SFNFH). This organization supplies approx. 90% of timber to the Polish market. The SFNFH has been in existence, in a slightly modified form, since 1924 (currently it manages 7,609,500 ha of Polish woodlands). Furthermore, 90% of SFNFH revenues are derived from timber sales. The amount of revenues of forest holdings depends on economic factors, such as timber prices, as well as non-economic variables including the quantity and quality of timber supplied to the market. The quantity and quality of timber assortments results from the sustainable forestry policy, natural conditions including soil characteristics, the production capacity of forest sites, as well as the adopted sylvicultural and environmental protection priorities. Coniferous forest sites are the dominant site type in the woodlands managed by the SFNFH (49.6%), with Scots pine stands being the most prevalent (60.1% by area). The other tree species of economic significance include: oaks (8.5% by area), birches (6.5%), Norway spruce (5.7%), European beech (6.4%), alders (4.8%), silver fir (2.8%), and aspen (0.4%). The mean age of SFNFH stands is 60 years, with the greatest proportion of stands in the 3rd and 4th age classes, accounting for 21.4% and 19.6% of the total, respectively. Stands that are more than 80 years old constitute 26% of all forests managed by the SFNFH [56]. The gross growing stock volume of roundwood in SFNFH forests is 2,065,656,000 m^3, which translates into an average of 290 m^3/ha. The volume of timber supplied to the market by the SFNFH is rising; in the years 2005–2021, the amount of timber sold increased by 26%, from 28,164,090 in 2005 to 38,064,900 m^3 (including 36,441,300 m^3 of roundwood) in 2021 [57,58].

2.2. Data Source

The study material consists of quarterly time series of the net prices of roundwood (W0) for the years 2005–2021. Data were obtained from the State Forest Information System.

In order to ensure the comparability of timber prices across EU countries, mean prices were given in nominal values and converted to euros according to the quarterly exchange rates published by the National Bank of Poland [59].

2.3. Methods

The paper compares classical models (ARIMA, ETS, BATS, TBATS), the Prophet model, and RBF and MLP neural networks. For each estimation method, we computed forecasts up to 12 steps ahead, with one step corresponding to one quarter. This forecasting horizon, which also constituted a test set for ANNs, was the most useful for assessing the quality of models. In the case of annual forecasts (4 steps ahead), quality evaluation may be attributable to chance, and thus unreliable. Predictions were verified and compared with one another using universal quality metrics for time series forecasts, including the root mean square error (RMSE) and the mean absolute error (MAE).

The applied methodology was fully automatic. First of all, automatic algorithms can handle univariate time series rapidly and efficiently adjusting model parameters, and so computation can be achieved within reasonable time. Traditional methods require human control and are time-consuming. In contrast, automatic algorithms provide models within a shorter time frame. In some areas, automatic machine learning performs less well or outperforms traditional models [60].

The non-seasonal part of the ARIMA model is denoted as (p, d, q), where p is the number of the autoregressive terms, q denotes the number of the moving average terms, and d indicates the number of differences required for stationarity. The seasonal part of the ARIMA model is denoted as (P, D, Q)m, where m = number of observations per year (Table 1). For ARIMA, we used automatic ARIMA models with the best levels of AIC, corrected AIC, or BIC [39].

Table 1. Estimated ARIMA models for roundwood prices.

Species	ARIMA
	(p,d,q) (P,D,Q)$_m$
Oak	0,1,1 (1,0,0)$_4$
Pine	1,1,0
Beech	1,0,1
Birch	0,1,0
Alder	2,1,1
Spruce	0,1,0

Analysis of the Polish timber market shows that timber prices in Poland are characterized by seasonality, with seasonal effect differentially affecting different assortments and tree species [35]. For the ETS state–space model, we used the algorithm proposed by Hyndman et al. [61,62]. A three-character string-identifying method is used in the framework terminology: the first letter denotes the error type (A, M or Z); the second letter denotes the trend type (N, A, M or Z); and the third letter denotes the season type (N, A, M or Z). In all cases, N = none, A = additive, M = multiplicative, and Z = automatically selected (Table 2).

BATS and TBATS models—both incorporating ETS state–space with Box–Cox transformation, ARMA errors, as well as trend and seasonal components—were introduced by De Livera et al. [63]. The fitted model is designated (omega, p,q, phi, $m_1, \ldots, m_j$) where omega is the Box–Cox parameter and phi is the damping parameter; the error is modeled as an ARMA(p,q) process and $m_1, \ldots, m_j$ list the seasonal periods used in the model (Table 3).

Table 2. Estimated ETS models for selected roundwood prices.

	ETS		
Species	**Error**	**Trend**	**Season**
Oak	M	N	A
Pine	M	N	N
Beech	M	N	N
Birch	M	N	N
Alder	M	N	N
Spruce	A	N	N

Table 3. Estimated BATS/TBATS models for selected roundwood prices in Poland.

Species	BATS				TBATS			
	Omega	**p,q**	**phi**	**$m_x \ldots m_j$**	**Omega**	**p,q**	**phi**	**$m_x \ldots m_j$**
Oak	0.659	0,0	1	4	0.615	0,0	-	4,1
Pine	1	0,0	-	-	1	0,0	-	-
Beech	1	0,0	-	-	1	0,0	-	-
Birch	0	0,0	-	-	0	0,0	-	-
Alder	0.021	0,0	0.8	-	0.021	0,0	0.8	-
Spruce	1	0,0	-	4	1	0,0	-	4,1

The Prophet model, which is also fully automatic, was developed by Facebook [64]. It is of the following form:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t,$$

where $g(t)$ stands for a piecewise–linear trend (the "growth term"), $s(t)$ reflects the various seasonal patterns, $h(t)$ captures holiday effects, and εt is a white noise error term.

The applied automatic forecasting procedure tested each model on a given time series and selected the best one based on the Akaike (AIC) and Bayesian (BIC) information criteria (Table 4):

$$AIC = 2k + \left[\ln\left(\frac{RSS}{n_{obs}}\right)\right]$$

$$BIC = n_{obs}\ln\left(\sigma^2\right) + k\ln(n_{obs})$$

where *AIC* is the Akaike information criterion, *BIC* is the Bayesian information criterion, k is the number of free parameters, *n_obs* is the number of observations, RSS is the residual sum of squares, and σ^2 is the error variance.

Table 4. Model selection based on AIC or BIC values.

Species	ARIMA		ETS		BATS	TBATS
	AIC	**BIC**	**AIC**	**BIC**	**AIC**	**AIC**
Oak	368.81	374.83	430.37	444.54	429.11	440.71
Pine	278.31	282.32	353.93	360.01	350.48	350.48
Beech	263.88	271.98	343.19	349.27	333.70	333.70
Birch	265.87	267.88	336.44	342.52	334.97	334.97
Alder	262.75	270.78	338.57	344.65	331.67	331.67
Spruce	284.13	286.14	358.75	364.83	352.06	349.42

Finally, the tested ANNs included multi-layer feedforward perceptron (MLP) and radial basis function (RBF) models [65,66]. The MLP networks adopted in this study had a different structure for each model (Table 5). The conjugate gradient and steepest descent training algorithms were used to train the networks.

Table 5. Type and structure of ANN models for each species: MLP—feed-forward multilayer perceptron, RBF—radial basis function, BFDS—Broyden–Fletcher–Goldfarb–Shanno algorithm, RBFT—the default learning algorithm for RBF networks in the Statistica solver; the number of training epochs is provided in brackets, SOS—sum of squares.

Species	Number of Neurons (Input-Hidden-Output)	Learning Algorithm and Iterations	Error Function	Activation Function (Hidden Layer)	Activation Function (Output)
Oak	MLP 5-18-1	BFGS 103	SOS	Tanh	Logistic
	RBF 5-29-1	RBFT	SOS	Gauss	Linear
Pine	MLP 5-9-1	BFGS 56	SOS	Exponential	Logistic
	RBF 5-26-1	RBFT	SOS	Gauss	Linear
Beech	MLP 5-15-1	BFGS 27	SOS	Exponential	Logistic
	RBF 5-25-1	RBFT	SOS	Gauss	Linear
Birch	MLP 5-16-1	BFGS 32	SOS	Exponential	Logistic
	RBF 5-29-1	RBFT	SOS	Gauss	Linear
Alder	MLP 5-15-1	BFGS 12	SOS	Exponential	Logistic
	RBF 5-29-1	RBFT	SOS	Gauss	Linear
Spruce	MLP 5-20-1	BFGS 33	SOS	Logistic	Sinus
	RBF 5-21-1	RBFT	SOS	Gauss	Linear

The model can be formally stated as follows:

$$y = F\,(k-1, k-2, \ldots, k-N, \ldots) + \varepsilon t$$

where k is the dependent variable of interest and ε is the error term. The function F is nonlinear; in our approach, F has the form of an MLP or RBF neural network.

Input data contained information about past timber prices separately for each of the studied species (types of wood), with data about future prices being the network output. Repeated random subsampling validation was used for each ANN (both MLP and RBF models). A total of 15% of randomly chosen data from the learning data set were used for model validation. Validation sets are used to stop training early if the network performance on the validation vectors fails to improve. One round of cross-validation was used to compare the results across different ANNs. We tested the different number of internal connections, number of layers, epochs, learning algorithms, and activation functions. All data from the testing set were used for cross-validation. The dataset was divided into two subsets with 52 teaching steps and 12 steps ahead for testing medium-term forecasts. Then, RMSE and MAE were computed for a three-year forecast horizon.

Each ANN model given in Table 5 was trained 100 times with different initial weight sets. A slight relationship was observed between the initial weights and the final training results after meeting the stop criteria. However, it was found that different initial weight sets did not considerably affect RMSE, with the standard deviation for the errors being less than 0.1%.

The following model statistics were calculated to score the models:

$$MSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}$$

$$MAE = \frac{1}{N}\sum_{i-1}^{N}|y_i - \hat{y}|$$

where $\hat{y}$—predicted value of y; $\overline{y}$—mean value of y.

Numerical experiments were implemented in R version 4.1.2 and Statistica version 13.1 [67,68].

3. Results

The highest mean price was found for oak roundwood (126.65 € m^{-3}) and the lowest for birch roundwood (43.18 € m^{-3}). Oak wood was also characterized by the largest price variability (23.24%) and the greatest difference between maximum and minimum prices (approx. 103 € m^{-3}, or 55%). Alder wood prices revealed the lowest difference between maximum and minimum levels (35%) as well as the greatest stability (9.78%) throughout the period of study. Standard deviation values indicate the greatest volatility for oak wood prices (29.44%), and the lowest volatility for alder and beech wood prices (4.46% and 4.96%, respectively, Table 6).

Table 6. Descriptive statistics for price time series of roundwood (W0) from the most important forest tree species.

Species	N	Mean	Median	Min	Max	Variance	SD	CV
Oak	68	126.65	117.67	86.32	189.12	866.51	29.44	23.24
Pine	68	55.57	56.95	41.03	71.66	39.59	6.29	11.32
Beech	68	47.99	48.88	34.16	57.75	24.60	4.96	10.33
Birch	68	43.18	44.39	30.31	52.58	28.88	5.37	12.45
Alder	68	45.61	46.80	35.51	54.31	19.90	4.46	9.78
Spruce	68	59.04	60.91	42.37	72.59	51.83	7.20	12.19

Oak wood commanded the highest prices in Q1 (130.59 € m^{-3}) and exhibited the highest price volatility in Q4 (SD = 31.90 € m^{-3}, CV = 25%); the lowest oak wood prices were found in Q2 (124.20 € m^{-3}) at the lowest volatility (SD = 27.96%). Pine wood was the most expensive in Q4 (56.20 € m^{-3}), and the cheapest in Q1 (55.18 € m^{-3}) at the lowest volatility (10.17%). Beech wood commanded the highest prices in Q1 (48.63 € m^{-3}), and the lowest in Q3 (47.40 € m^{-3}). The highest prices (43.80 € m^{-3}) and volatility (CV = 14.24%) of birch wood was found in Q2, and the lowest in Q4 (42.93 € m^{-3}). Spruce wood was the most expensive in Q1, and the cheapest in Q3 (at the lowest volatility, SD = 6.98 € m^{-3}) (Figure 1).

The models used for roundwood price forecasting exhibited different error levels, reflecting varying degrees of fit, depending on the type of wood (Appendix A, Figure A1). Ex-post measures of forecasting accuracy were based on comparisons of predicted and actual prices. Table 7 shows a summary of RMSE and MAE values and the efficiency of timber price forecasting for all models for the years 2019–2021.

The best forecasts with low error values were obtained for almost all species of roundwood using MLP. The ARIMA model, which is widely used for predicting timber prices, generated the best predictions for birch and alder roundwood (with MAE and RMSE amounting to EUR 0.87 m^{-3} and EUR 1.06 m^{-3} for birch and EUR 1.89 m^{-3} and EUR 2.34 m^{-3} for alder, respectively). Additionally, differences between MAE and RMSE were slight, which indicates a low level of deviations in the forecasted period and small errors (differences between predicted and actual prices were low). ARIMA performance was the weakest for oak roundwood. As compared to ARIMA, the ETS model exhibited a better fit for alder wood (MAE = EUR 0.86 m^{-3}, RMSE = EUR 1.06 m^{-3}) and beech wood (MAE EUR 1.6 m^{-3}, RMSE EUR 2.06 m^{-3}), while forecast results for spruce, oak, birch, and pine roundwood were like those obtained with ARIMA.

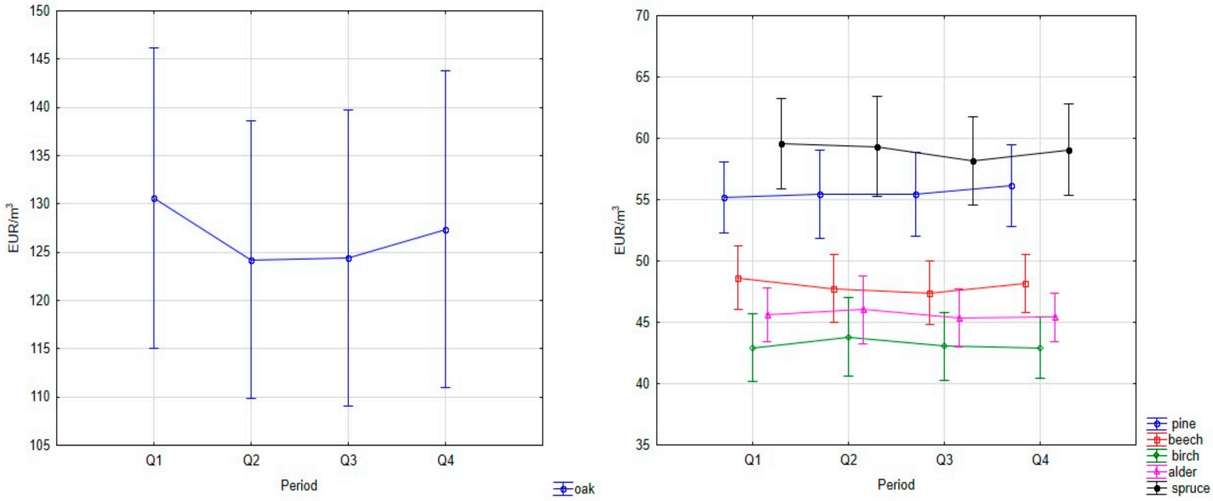

Figure 1. Mean quarterly prices of roundwood from the most important forest tree species in the years 2005–2021.

Table 7. Accuracy measurements for ANN MLP, ANN RBF, ARIMA, ETS, BATS, TBATS, and Prophet models.

Species	Error	ARIMA	ETS	BATS	TBATS	Prophet	ANN RBF	ANN MLP
				€ m^{-3}				
Oak	MAE	7.8889	7.4821	17.7059	7.7329	1354.5853	8.9207	4.7401
	RMSE	10.8107	10.3894	19.0721	10.6630	1460.4362	10.4501	8.0902
Pine	MAE	2.7169	2.7819	2.7317	2.7317	386.6866	2.6166	2.2107
	RMSE	4.6619	4.8343	4.7253	4,7253	432.2114	3.9172	2.8290
Beech	MAE	3.3621	1.5970	1.8388	1.8388	290.7703	2.6166	2.3099
	RMSE	4.2054	2.0649	2.0608	2.0608	321.9117	3.9172	2.7094
Birch	MAE	0.8678	0.8678	0.8582	0.8582	281.5886	2.4009	2.6798
	RMSE	1.0596	1.0596	1.0432	1.0432	303.6497	3.2924	2.9346
Alder	MAE	1.8797	0.9073	1.5540	1.5541	308.5003	2.3340	1.8849
	RMSE	2.3437	1.2806	2.0771	2.0771	340.0781	3.4739	2.4017
Spruce	MAE	3.4664	3.4663	3.3882	3.4591	395.7933	3.7613	2.4433
	RMSE	5.1926	5.1926	5.2509	5.2359	457.5634	4.3509	2.5876

BATS and TBATS produced good forecasts for birch and alder roundwood, which were characterized by very low MAE and RMSE (especially in the case of birch wood).

The Prophet model led to the highest forecast errors and the lowest fit, and so it cannot be feasibly used with quarterly data in practice.

Both RBF and MLP models exhibited good performance, with MLP being the superior one. MLP had the best fit for spruce roundwood (MAE EUR 2.44 m^{-3}, RMSE EUR 2.58 m^{-3}), followed by oak wood (MAE EUR 4.74 m^{-3}, RMSE EUR 8.09 m^{-3}) and pine wood (MAE EUR 2.21 m^{-3}, RMSE EUR 2.83 m^{-3}). Good quality forecasts were also obtained for the other species of wood (Table 7).

These time series illustrate the prediction capacity of individual models in a more detailed way than forecast errors alone. Figures 2 and 3 present a comparison of the price trends generated by the analyzed models for the studied species.

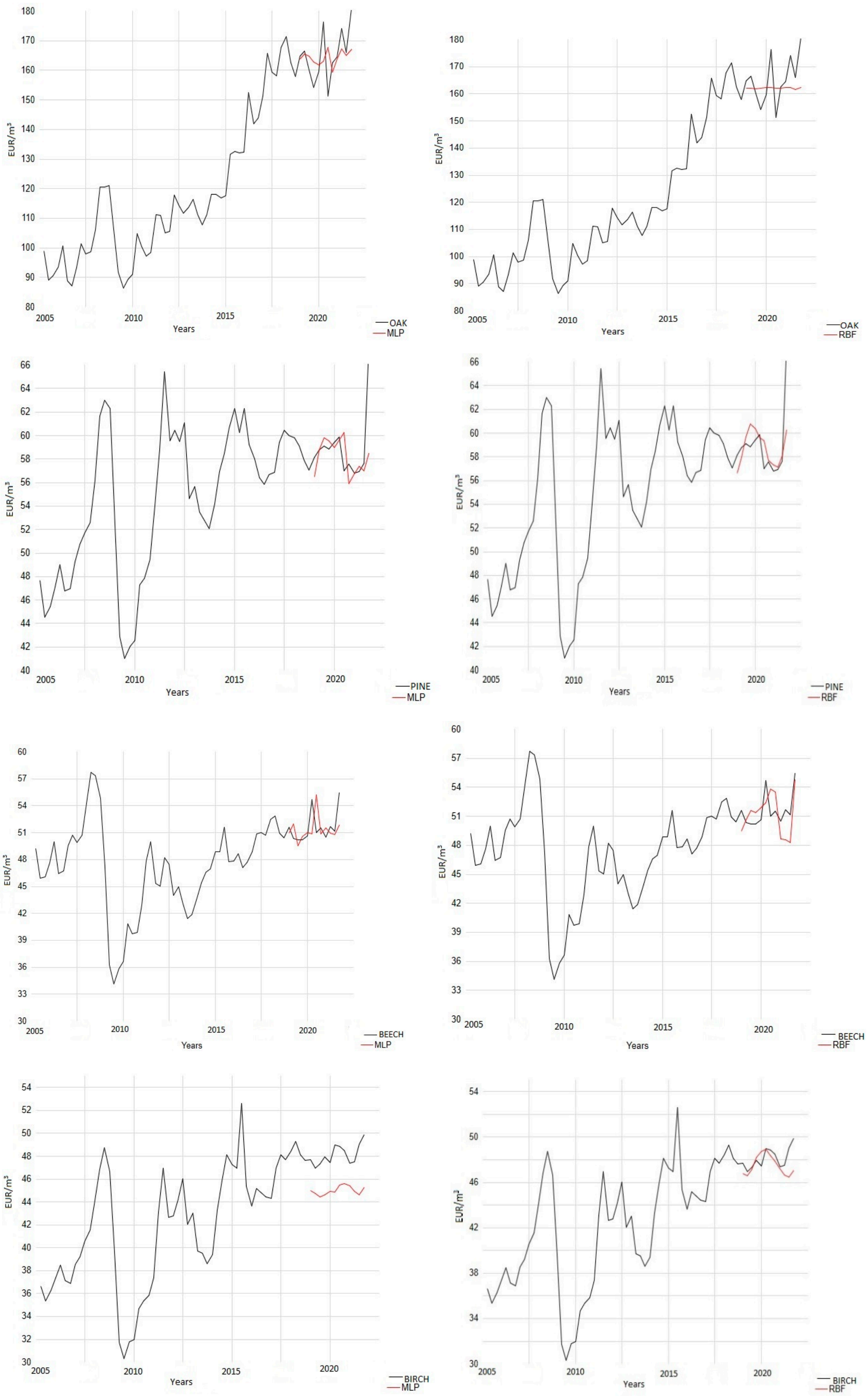

Figure 2. *Cont*.

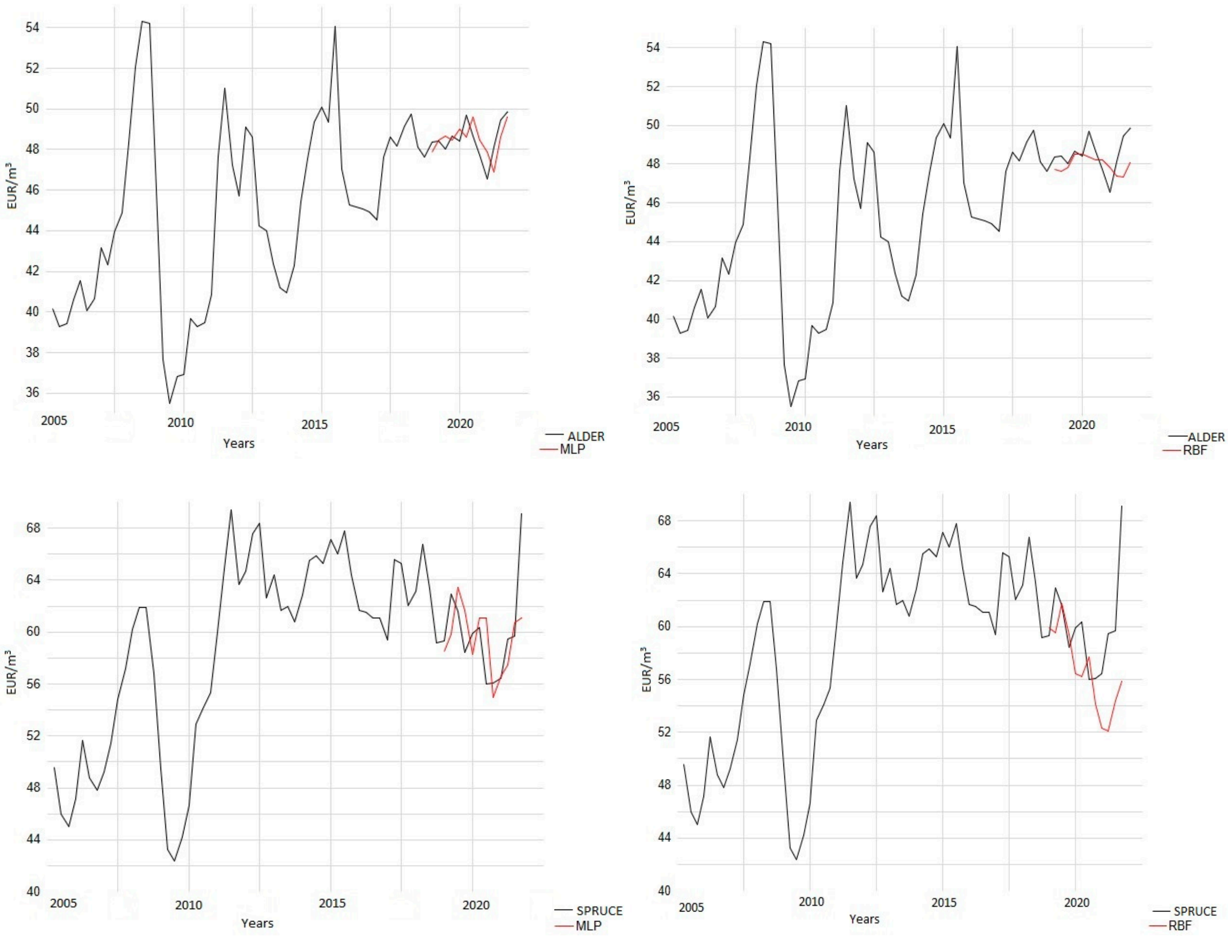

Figure 2. Simulation results for MLP and RBF models for each type of wood.

ANN models had a better fit to minimum and maximum values, while the classical models failed to predict an upward price trend in the last quarters of the study. In the case of alder and beech roundwood, the best two classical models underestimated prices and showed a bias toward average values. For the same species, BATS and ETS led to better quality forecasts, while ANN models revealed a much better fit to outliers.

Oak roundwood prices were best predicted by the MLP model, which had the best fit, while RBF was characterized by a bias toward average values, failing to reproduce an upward trend. TBATS and ETS models accurately indicated maximum prices, but failed to reflect price decreases. None of the studied models predicted the considerable oak wood price increase in the last quarter, although MLP did indicate a slight price growth.

In the case of pine wood, the best forecast fit was found for the RBF model, which indicated a clear upward price trend, even though the fit metrics would favor MLP.

RBF forecasts for beech wood were inferior to MLP forecasts (the former overestimated the initial quarters and underestimated the subsequent ones), but their predictions for the last quarter were the most accurate, identical to the actual values. The MLP model had the best RMSE and MAE metrics and indicated a price increase in the last quarter (but it still underestimated the magnitude of the increase).

In the case of birch roundwood, the MLP model reflected the direction of trends, but substantially under-forecasted the prices. Price levels were predicted with greater accuracy by the RBF model; it rendered an accurately smoothed trend, while underestimating prices in the last quarter. Classical models revealed a bias toward average values, failing to indicate an upward trend in the last quarter.

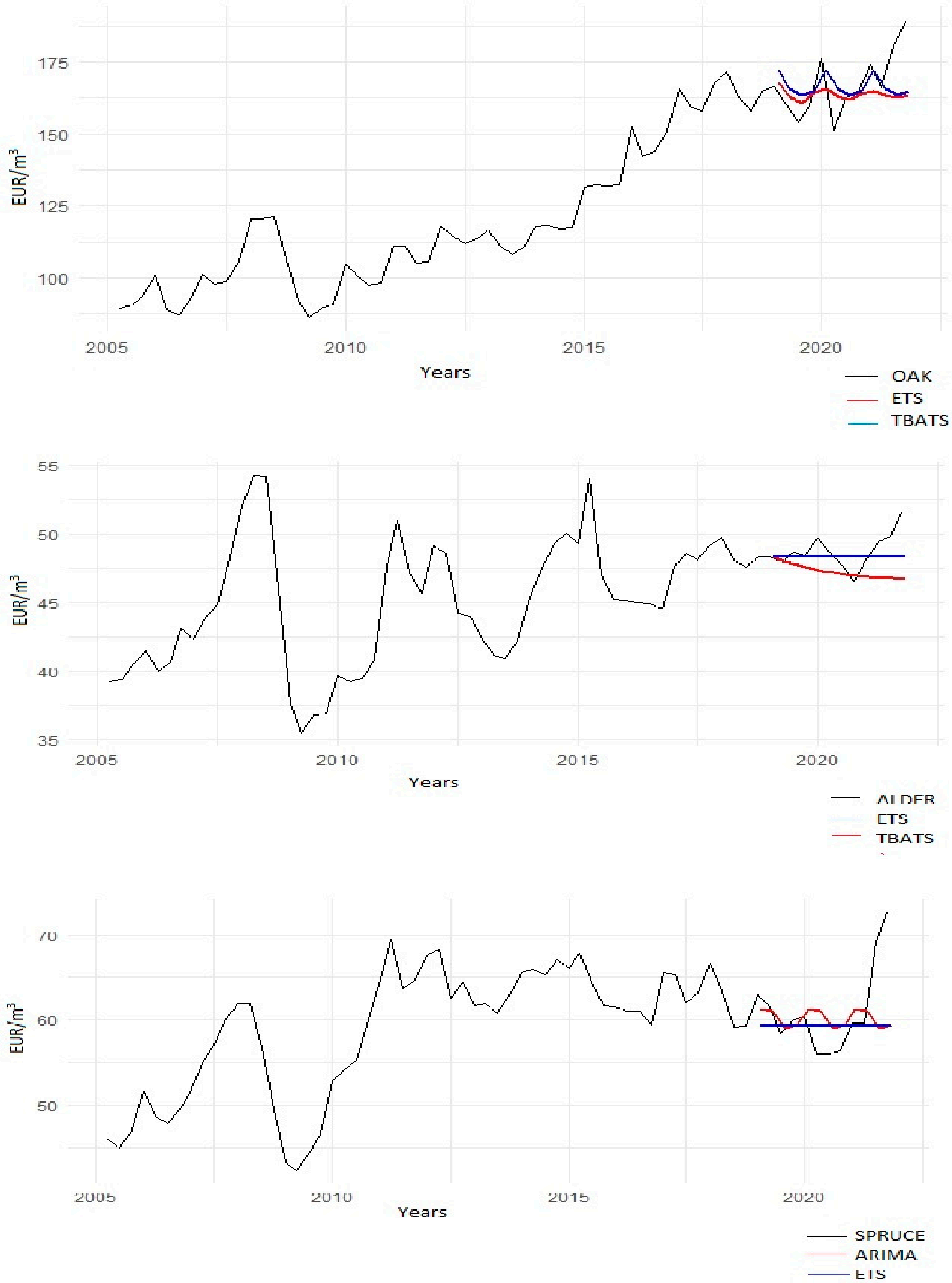

Figure 3. Simulations of the best classical models for oak and alder (ETS and TBATS) and for spruce (ARIMA and ETS).

The RBF model also produced good spruce forecasts, which reflected the directions of price changes, while underestimating prices, especially in the last quarters. The MLP model best reflected the shape of the price trend, while ARIMA was biased toward average values. BATS indicated price fluctuations, but did not reflect their actual values, especially for the last quarter (it forecasted a decrease, while the prices in fact rose).

4. Discussion

In the context of changes in forestry priorities and the adoption of a multifunctional model of forest management over recent decades, price analysis and forecasting in the primary timber market is of great significance for state-owned forest holdings, private forest owners, as well as the wood industry. Historical time series analysis and price predictions are important tools helping forest owners and managers make informed decisions on timber harvesting as well as forest sales [5,12].

Time series methods enable good prediction results without the need for substantial expenditures on data acquisition and analysis [27]. The choice of an appropriate forecasting technique depends on the presence of the following time series components: trend, seasonality, cyclicality, and random effects. Traditional time series methods such as ARIMA and ETS are designed to address single seasonality, but they fail to satisfactorily handle multiple seasonality effects. Our study indicates that in most cases ETS was superior to ARIMA, judging by error values. Michinaka et al. [19], who used ARIMA and ETS for forecasting monthly timber prices in Japan, mostly for 6- and 12-month periods, reported better performance for ARIMA. While both BATS and TBATS can be used to model time series with complex seasonal patterns, the latter is suitable for modelling non-integer seasonal frequencies, being based on trigonometric functions [63,69]. In turn, the unique characteristics of ANN models, such as adaptive capacity and nonlinearity, make them extremely useful for predicting a wide range of phenomena, including economic ones.

The applied classical and ANN models varied in their suitability for wood price forecasting. It should be noted that evaluation of the models may differ depending on the assessment metric used: RMSE, MAE, or a detailed comparison of prediction plots. This is attributable to the nature of these measures. RMSE, being based on exponentiation, is more likely to incur greater penalties in the case of larger differences between predicted and actual values and is also vulnerable to outliers. MAE, which is a weighted average of mean absolute errors of predictions, is more intuitive, but it does not penalize large forecasting discrepancies as much. Thus, the optimum models chosen on the basis RMSE will be good at estimating outliers. On the other hand, models selected using MAE can in general accurately predict prices, but may be more prone to errors when encountering outliers. In this situation, MLP models were substantially superior to the others, which is visible in detailed forecast charts. ANN models had one hidden layer. The number of neurons in the hidden layer ranged from 15 to 29. The mean number of neurons for MLP (average 15.5) was lower than for RBF (average 26.5). The activation functions for the MLP model for pine, birch, beech, and alder were used as exponential function, and for oak (Tan), spruce—logistic. In the input layer, the logistic function was used, except for spruce (Sin). The classical models (ARIMA, ETS, BATS, and TBATS) tended to smooth the forecasted price trends and bias them toward average values. Another advantage of ANN models is that they replace programming with a learning process, due to which they can rapidly and accurately adapt to empirical data. Thus, if a price forecast is required at short notice, ANN models are recommended as they lead to the most accurate predictions without the need for extra information. In contrast, the calibration of classical models is more demanding and time-consuming.

In the Polish market, there are considerable differences in timber prices and supply between different species of wood [35]. As shown by Tian et al. [70], the supply of timber does not always affect its price. Research on the price elasticity of timber supply from different regions in the United States and Europe have produced mixed results. Additionally, the effects of market factors on the prices of timber are not evident or invariable, and may differ between softwood and hardwood. As observed by Luppold [71], an understanding of the economic determinants of softwood markets is important for developing timber management plans. Furthermore, the factors enabling successful hardwood management may be dissimilar from those prescribed for softwood [71]. The prices of timber from different tree species may differ due to their uses in various sectors of the economy and due to advanced timber processing opportunities. Hardwood differs from softwood in important technological aspects, with the latter being more desirable, e.g., in the construction industry.

The basic type of timber offered by the SFNFH in Poland is pine wood (which accounts for 60% of the overall supply). Among the models used for the forecasting of pine wood prices, ANNs exhibited the best performance, with MLP being superior in terms of forecast errors, and RBF better reflecting price increases. The classical models were less useful. In spruce wood forecasting, the best results were obtained for MLP, which accurately rendered price fluctuations despite the fact that spruce prices were under pressure from oversupply, especially in the years 2018–2019. The prices of spruce roundwood in Poland were also cointegrated with prices in the Czech and Austrian markets [10].

The prices of oak roundwood in Poland were the least sensitive to negative economic data, and exhibited a steady growth trend, especially from 2013 to 2021. According to Luppold [71], the factors tangibly affecting oak wood prices include applicability (durability), esthetic quality, consumers' emotional responses to this kind of wood, as well as fashion. Analysis of the obtained forecasts revealed the highest MAE and RMSE values for this species. The lowest errors were found for MLP, and it was the only model that predicted price increases in the last quarters of the study. TBATS models (as well as, to some extent, ETS models) rather accurately reflected price changes and maximum prices, but underestimated minimum prices and failed to capture the final upward trend.

Throughout the studied period, beech wood was characterized by a stable growth trend in Poland up to 2008, followed by a price decline, stagnation, and moderate price increases since 2017. While in the case of this species ETS revealed the lowest error values, ANN models were superior in terms of predicting price changes.

In Europe, except for the Baltics, the prices of birch roundwood are generally lower than those of softwood. Throughout the period of study, the prices of birch wood in Poland were lower than those of pine and spruce wood (e.g., by approx. EUR 10 m^{-3} and EUR 14 m^{-3}, respectively, in 2018). Birch wood prices were best predicted using ANN models, with RBF networks more accurately reflecting the level of price changes.

In the case of alder wood, the best forecasts were obtained using the MLP model, while the lowest errors were found for ETS predictions.

In general, our study results indicate the superiority of ANNs over the classical models in forecasting timber prices in the primary market. The ANNs exhibited a better fit and lower error terms. Koutroumanidis et al. [54], who forecasted the prices of fuelwood in Greece based on ARIMA and ANN models, found the latter to perform better due to lower RMSE and mean absolute percentage error (MAPE) values. In addition, the authors developed a hybrid ARIMA–ANN model using quantitative predictions for softwood from ARIMA. Analysis of errors revealed that the ARIMA–ANN model had a superior adaptive capacity and was able to predict future price movements more accurately than both ARIMA and a simple ANN model [54]. In turn, Lopes et al. [55] used long short-term memory (LSTM) networks to forecast lumber stock prices. The authors showed that neural networks effectively captured nonlinear temporal relationships. Their predictions were characterized by extremely low MSE, RMSE, and MAE values in the period of study divided into recession intervals marked by the 2008 financial crisis and the COVID-19 pandemic. To forecast the future consumption of wood products in Greece, Tigas et al. developed and trained an ANN using a variety of time series [72]. Finally, ANN was compared with a traditional ARIMA model in terms of forecasting teak wood prices, with the former being characterized by lower MAPE values and better prediction of turning points.

The COVID-19 pandemic with the resulting housing boom led to an increased demand for timber, which has caused a sharp upward trend in timber prices in recent quarters. Under conditions of the dynamically changing market situation, the classical prediction models analyzed in the present study did not capture that trend, and consequently yielded under-forecasted prices. In turn, ANN models predicted a growth trend for all kinds of timber (MLP), with some forecasts being extremely accurate (RBF). Since ANN models performed well under volatile circumstances, it seems that, given the current energy crisis triggered by the war in Ukraine, one should focus on developing and improving them for predicting timber prices and supporting decision-making processes in the timber market.

Siveran [73] stressed that ANN models are strongly dependent on the time series values immediately preceding the forecasted year, which makes market price predictions a challenging problem. The situation is further complicated by a large number of factors/variables that cannot be foreseen with certainty [74]. Malaty et al. [5], who studied the pine wood market in Finland, observed that in real-life situations, forecasting based solely on a time series approach is difficult as timber prices in primary markets are affected by a plethora of factors. These include endogenous variables: environmental factors (determining timber availability), forest management factors (affecting timber quality, quantity, and availability), economic factors (demand shaped by the prevalent economic situation), and political factors (arising from state interventions—environmental policies as well as taxes and customs tariffs) as well as exogenous variables linked to the situation in the regional and global markets. Moreover, it should be noted that climate change has led to the widespread occurrence of hard-to-predict extreme events. The droughts and gale-force winds impacting tree stands often cause an oversupply of timber and local decreases in its prices [74,75]. Therefore, the timber-selling process should be aided by appropriately selected and implemented methods for price forecasting, as well as models predicting timber demand and supply. In future research, projection forecasting, which ignores the effects of exogenous variables, could be supplemented with causal forecasting, which reflects the influence of exogenous factors on timber prices. For instance, Riis [15] developed a model for forecasting timber prices in Denmark with a corresponding Swedish price series, using exogenous variables such as gross national product and a building activity index. He et al. [48] showed that deep learning models generally give more accurate lumber predictions than machine learning models. Among the seven models (SVM, Random Forest, XGBoost, CART, ANN, RNN, and CNN), the ANN model provides the best performance, followed by the RNN model. They imply that the Google Trends index, which reflects the dynamic changes of the interest and attention from the public, can provide enough information to be good predictors in nowcasting lumber futures prices.

In other domains, machine learning models and deep learning models were widely used for time series forecasting. Bhandari et al. [76] uses a long short-term memory (LSTM), a particular neural network architecture, to predict the next-day closing price of the S&P 500 index. The results show that the single-layer LSTM model provides a superior fit and high prediction accuracy compared to multilayer LSTM models. Luo et al. [77] use hybrid LSTM–ELM models to predict bitcoin prices. Zhang et al. [78] proved that hybrid PSO–ELM and GA–ELM models could forecast copper price with higher accuracy and reliability over the traditional ELM and ANN models. Salamai [79] used a deep learning framework (LSTM) for the predictive modeling of crude oil price for sustainable management in oil markets.

Scientists are developing more and more precise and advanced predictive models. Although there is a wide range of single models proposed for time series forecasting, they are not promising approaches that can be applied on all situations with desired performance. Hybrid methods are appropriate alternative that can yield superior performance compared to individual options [80]. Recently, in time series modeling, new hybrid models were used [81–84]. The greatest progress and advanced hybrid models are as follows: LSTM-ALO, ANFIS-GBO, ELM-PSOGWO, LSSVM-IMVO, LSSVR, and SVR-SAMOA, which are used in forecasting natural phenomena, hydrology, and pan evaporation [85–91].

It is likely that forecasts taking into account exogenous variables may be more useful in economic practice due to the possibility of detecting associations between prices and factors such as some macroeconomic indicators. However, there is only limited research in the literature that identifies the most effective economic and technical variables for predicting timber prices using machine learning models. This is a major limitation in the use of hybrid models due to the limited knowledge of exogenous variables (input data to the model). Exogenous variables should be identified and used in advanced hybrid models.

Managers responsible for timber sales should pursue flexibility in adjusting the quantity and structure of timber assortments to the changing economic conditions [92,93].

5. Conclusions

The studied models revealed different degrees of suitability for forecasting prices in the primary timber market. The best price projection results, as evaluated by fit to data and measures of error (MAE and RMSE), were obtained for the MLP model. Values for errors models for oak (MAE EUR 4.74 m^{-3}, RMSE EUR 8.09 m^{-3}), pine (MAE EUR 2.21 m^{-3}, RMSE EUR 2.83 m^{-3}), birch (MAE EUR 2.68 m^{-3}, RMSE EUR 2.93 m^{-3}), alder (MAE EUR 1.88 m^{-3}, RMSE EUR 2.40 m^{-3}), and spruce (MAE EUR 2.44 m^{-3}, RMSE EUR 2.58 m^{-3}). While the classical models exhibited low error values for alder and beech (ETS: MAE EUR 0.90 m^{-3} and EUR 1.59 m^{-3}, RMSE EUR 1.28 m^{-3} and EUR 2.06 m^{-3}, respectively) and birch (BATS and TBATS: MAE EUR 0.85 m^{-3}, RMSE EUR 1.04 m^{-3}), they tended to be biased toward average values and produce underestimates (they did not reflect outliers—minimum and maximum values).

ANNs indicated upward wood price tendencies in all cases, and so it seems that they can be successfully used by timber market actors as universal methods of price forecasting. Due to recent developments, the past several months have seen spectacular increases in timber prices, not predicted by any model except RBF for beech wood. Despite its well-known limitations, projection-type price forecasting constitutes a relatively fast way of obtaining approximate information about future timber prices.

Studies have shown that neural networks allow for obtaining more precise results, compared to the classical methods commonly used in forecasting timber prices (e.g., ARIMA). ANN models can be improved to additionally reflect the effects of exogenous variables (e.g., macroeconomic data and other economic indicators). The optimization of such models requires further research on larger test sets of greater resolution (using monthly data), involving the adjustment of network structure and teaching parameters to make them even more useful in timber price forecasting.

Analyses showed that the accuracy of price forecasts vary across species of wood. Indeed, the timber market is not homogeneous, with its softwood and hardwood segments being rather dissimilar, especially in terms of price levels and price change amplitudes. In addition to the application of potential and functional properties of timber from different tree species, wood prices are affected by multiple global, national, and local factors. As these factors are highly changeable across time and space, in-depth analyses of them are time-consuming and do not guarantee high prognostic accuracy.

Analyses should continue taking into account new algorithms and hybrid models in order to develop the most optimal solutions enabling the precise forecasting of changes in wood prices. The next sections (research) to follow will be implementing deep learning neural networks in scheduling, simulation of economics, and technical parameters to solve complex problems.

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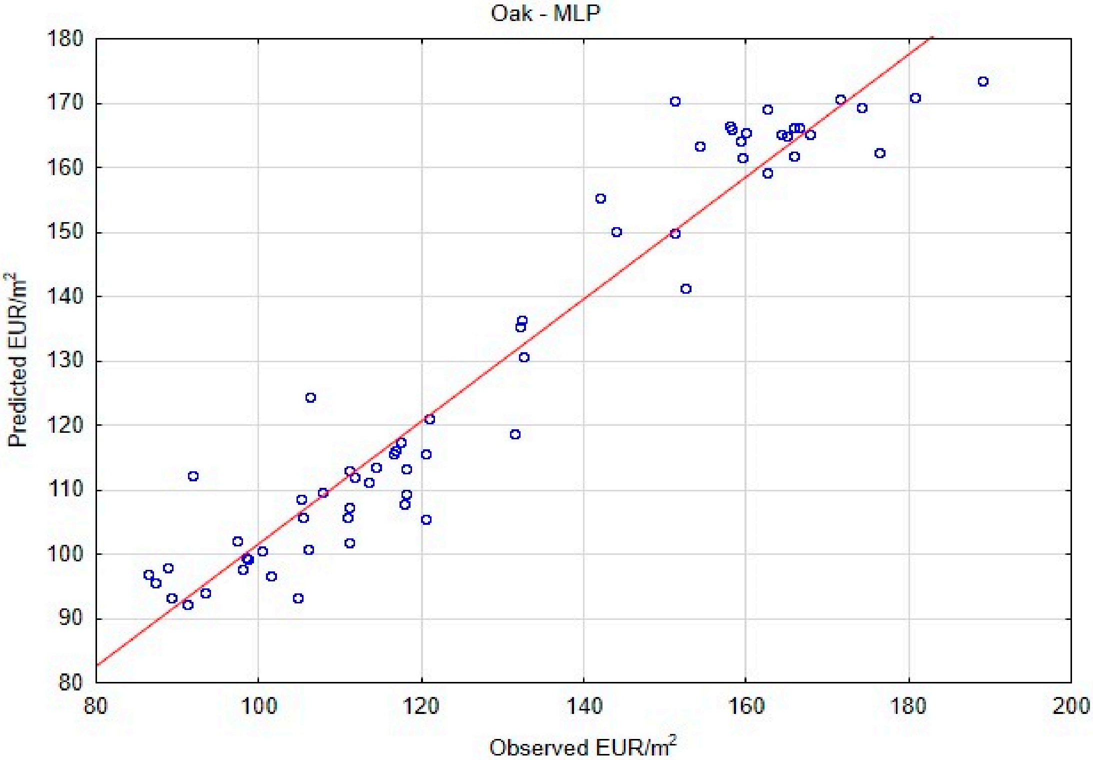
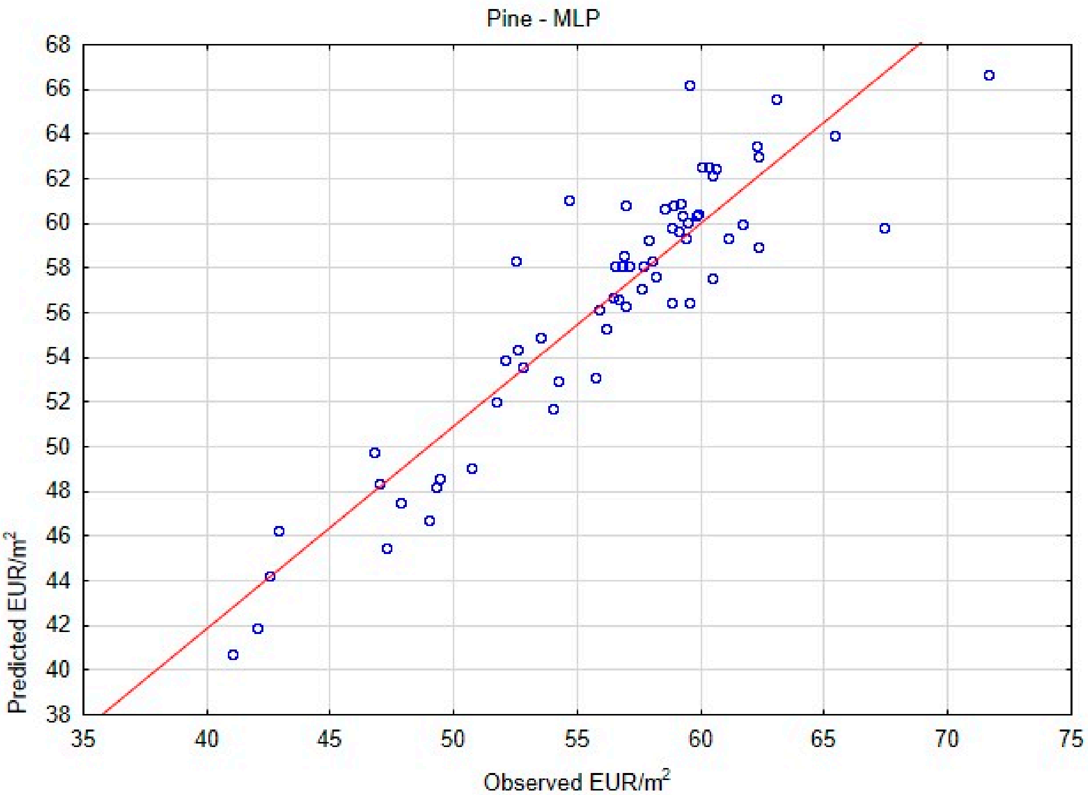
Data Availability Statement: http://drewno.zilp.lasy.gov.pl/drewno/ (accessed on 1 June 2021).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A





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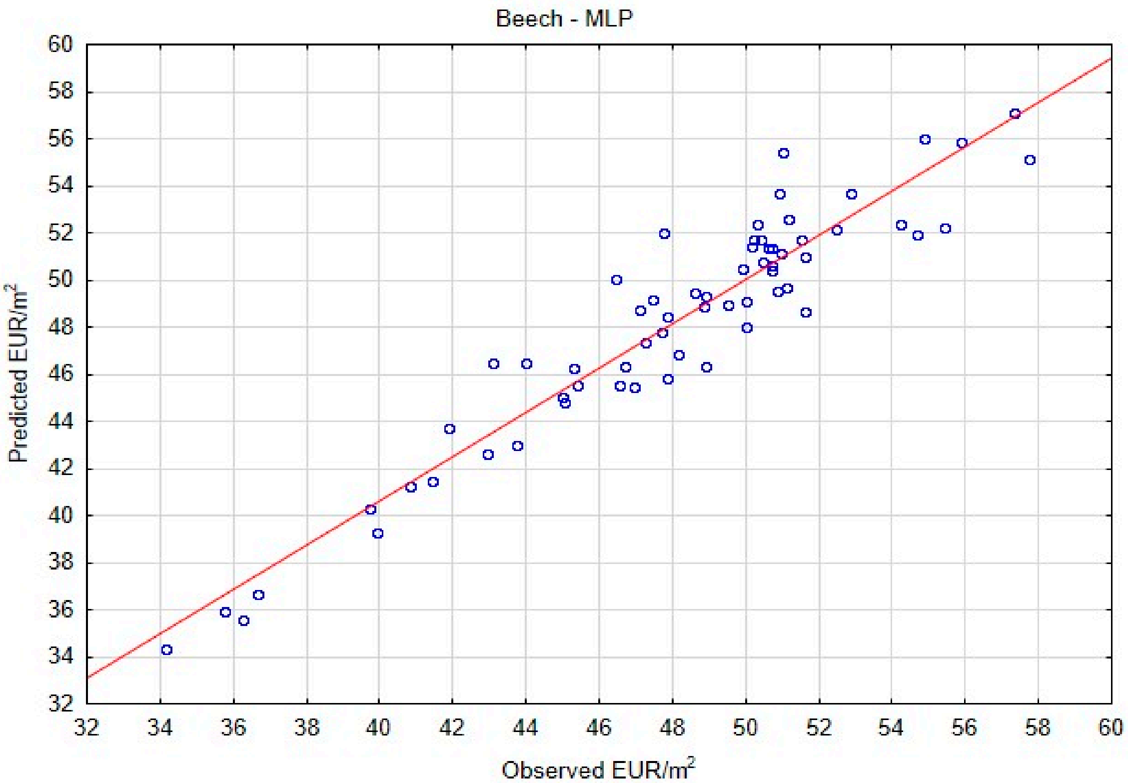

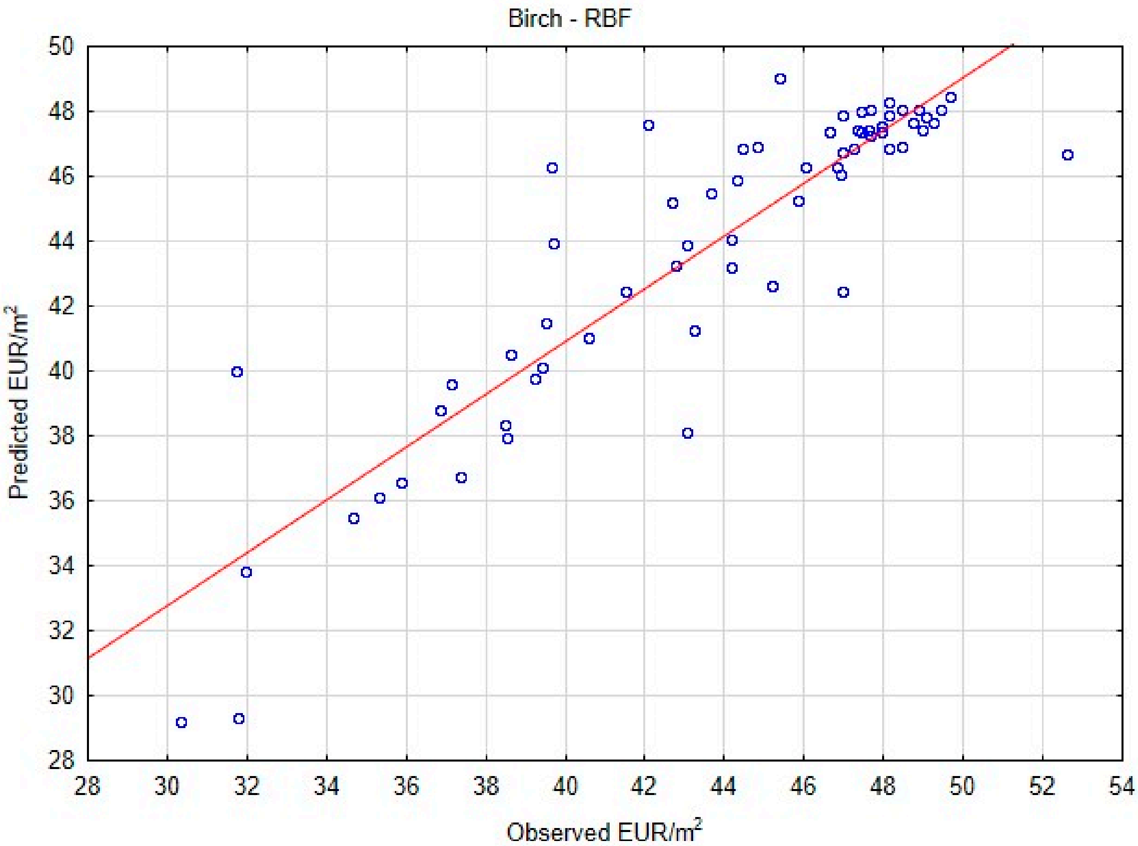

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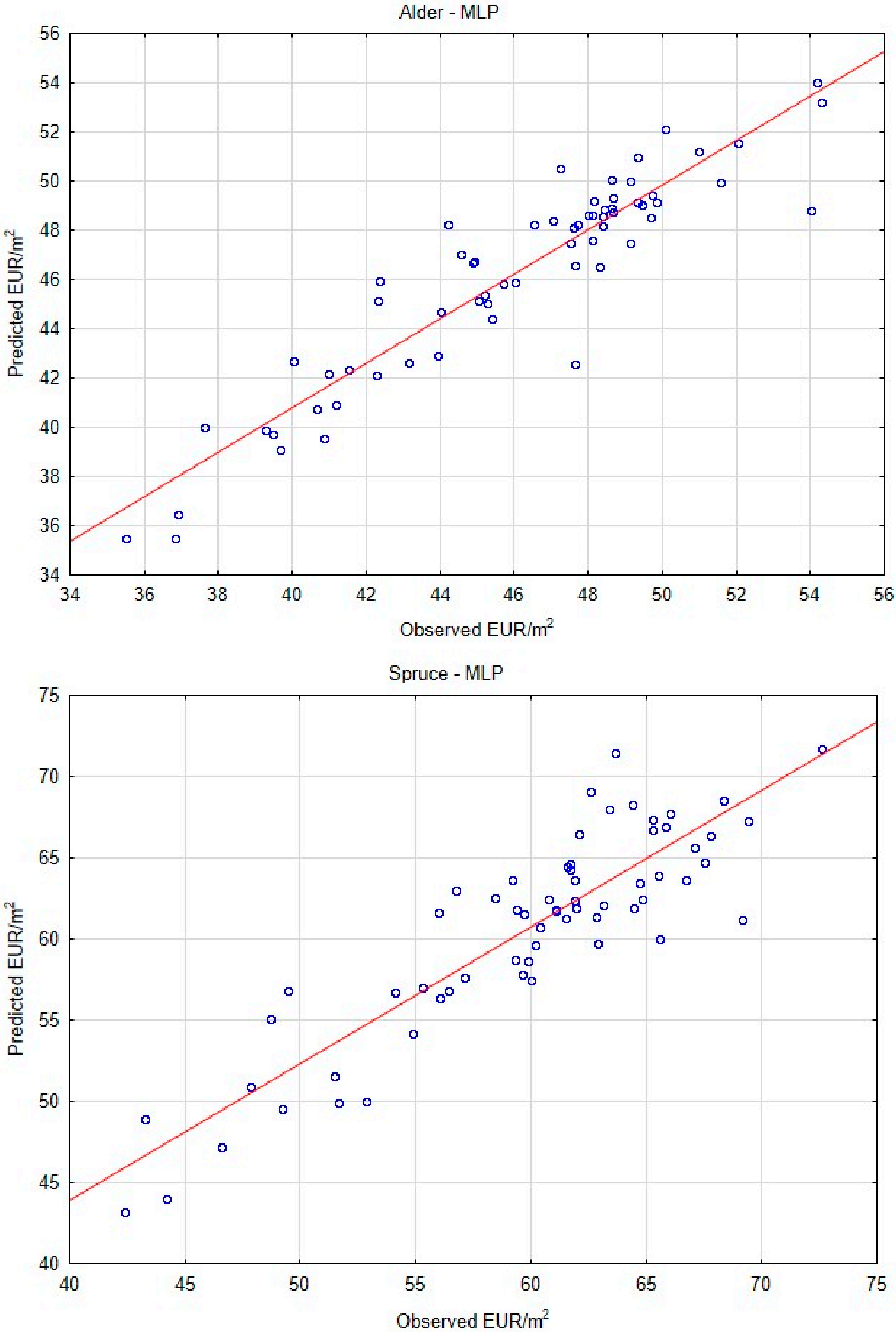

Figure A1. Residuals versus fitted values for the best ANN models for the timber price of each species.

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