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Neuronal Network based modelling of demand and competing use of forestry commodities for material and energy use

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Abstract

A methodology for development of scenarios for multiple forestry commodities quantities and prices through a nonlinear autoregressive neuronal network model with additional exogenous input parameters is presented. By mapping all possible interdependencies between forestry commodities and commodity prices, this approach shall enable to model the demand for different commodities and competing use for these commodities.
The presented model performs good in terms of input-output correlation (R=0,99) for all variables combined. The results point to the conclusion that the functional relation between CO_2-emission scenarios and biomass use can be captured by the modeling framework.

Keywords: forestry commodities, biomass, neuronal networks, long term scenarios

1. Introduction - How will demand and prices for competing forest products develop over time?

Model-based scenarios of the global energy sector predict with high agreement that both demand and international trade of biomass will increase strongly over the coming years and decades. Competition for forestry products (and by-products), particularly for low-grade goods, will increase in the coming years due to the growing demand for bioenergy [1]. Modelling and describing the competition between material and energy use of biomass fractions is thus of crucial importance in energy-economic assessments and scenario-building but is, so far, in the fewest models mapped in detail. It is therefore important to take

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into account cross-dependencies of commodities and prices; e.g. how do sawnwood prices affect wood fuel prices and quantities?

In scientific literature various approaches exist to formulate demand equations and interdependence due to competing uses [2]. The complexity of the factors and interactions, which influence the demand for commodities from the forestry sector and biogenic fuels (as well as in principle all products and services), can, in general, only be captured to a certain degree by model equations. Usually far-reaching assumptions about the function form of demand need to be made.

Artificial Neuronal Networks (ANN) are able to model demand patterns with uncertain function form and have shown good performance in time-series prediction in various applications [3][4][5][6]. Typically, neuronal networks are used to generate a single output variable (e.g. a forecast of a single commodity). In this paper an innovative methodology to develop scenarios of demand and future prices of multiple forestry commodities through nonlinear autoregressive neuronal network with additional exogenous input parameters is presented. By simultaneously and iteratively calculating the set of output variables based on the previous output, and therefore mapping all possible interdependencies between commodities and commodity prices, this approach is able to model competing use of for commodities.

2. Discussion of input data and data set preparation

Historical data for this analysis are aggregated on a yearly basis from 1961 to 2011. An extensive SQL-database has been established, which is based on the FAO ForeStat database [7] and the World Bank's world development indicators (WDI) [8]. This global data set has been aggregated in a total of 30 world regions (see also figure 2) and several forest products (see figure 1). All quantities are calculated in tons and are, where necessary, converted. If not stated otherwise, commodities (e.g. given in coniferous and non-coniferous fractions) in the FAO Database are first converted on the most detailed level, using the specific conversion factors, and aggregated afterwards. A detailed description of commodities and commodity aggregates as well as conversion factors can be found in the FAO Yearbook [9].

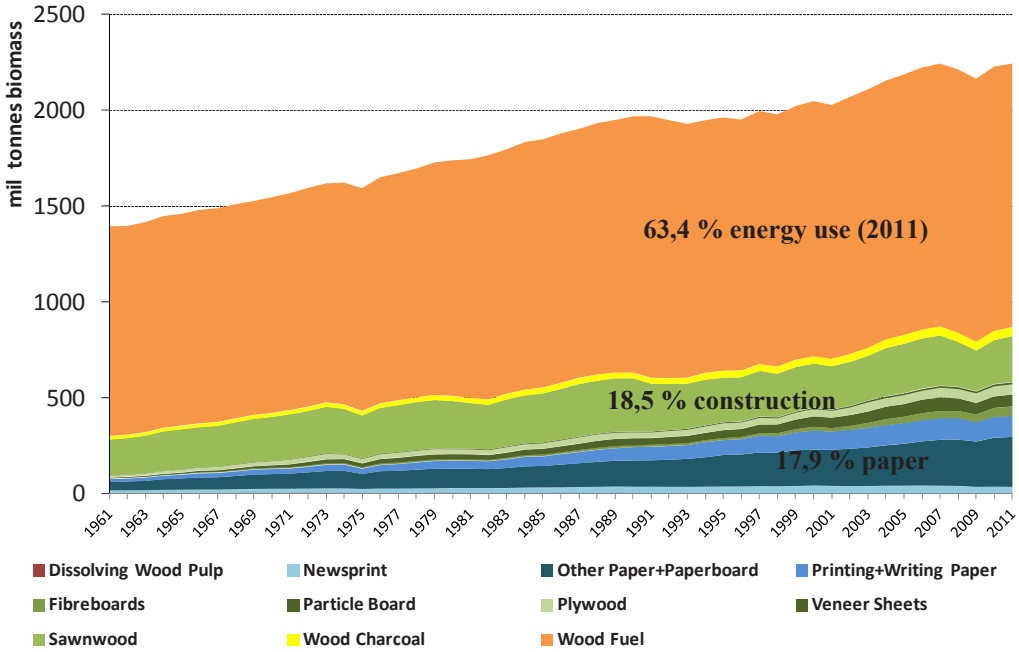

Figure 1 Global use of forest biomass (Data: FAOStat, Unit: mil. tons, own calculation, indicated percentages refer to the year 2011)

Figure 1 shows the historical development of global forest biomass use. Demand for every considered world region is calculated as production quantity plus imports minus exports. (Note that, on a global level, demand equals production, if transport and storage losses are neglected). Biomass directly used for energy purposes (wood fuel and wood charcoal) accounts for roughly two thirds (63.4%) of the global biomass production in 2011. This amounts approximately to a total primary energy supply (TPES) from global forest bioenergy use of 25 EJ. This compares to the International Energy Agency's (IEA) World Energy Statistics and World Energy Outlook TPES from traditional biomass of 30.7 EJ/yr, based on national databases [10]. In the SRREN is further stated that though international forestry and energy data are the main reference sources for policy analyses, they are often in contradiction when it comes to estimates of biomass consumption for energy, because production and trade of these solid biomass fuels are largely informal.

Figure 2 shows the regional pattern of global biomass use aggregated in energy and material use in 2011. The largest quantities of forest biomass for energy purposes are used in less industrialized regions especially Africa, India, South-east Asia and South America.

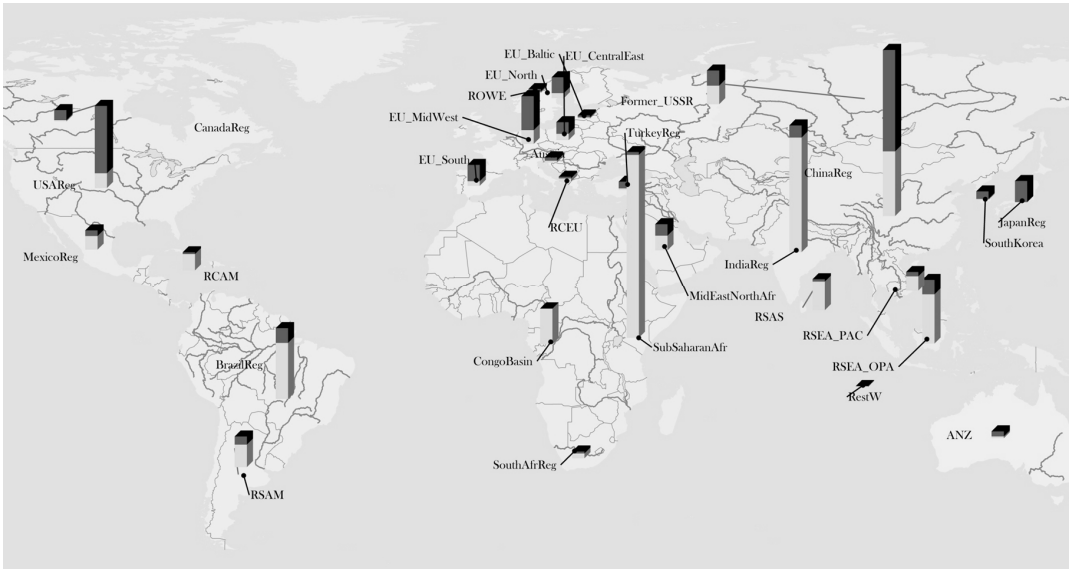

Figure 2 Demand for forest products aggregated in material use (dark green) and energy use (yellow) in 2011 for the 30 model regions (Data: FAOStat, tons, own calculation)

Exogenous input variables have been selected based on a literature review of underlying drivers in various forestry models. [1] The selected exogenous variables are population, GDP per capita, internet users (relevant for newsprint and paper fractions [11]), world GDP (same for all countries) and greenhouse gas emissions.

Scenario assumptions for the future development of the exogenous variables are based on the POLES reference scenario for population and GDP [12]. Internet use is assumed to linearly increase to reach 90% of population. In the high carbon scenario, carbon emissions are increasing linearly from 2011 on, in the low carbon scenario carbon emissions decrease by 30% from 2011 levels. Historical data are taken from the world development indicators.

To demonstrate the ANN methodology, this work will further focus on an analysis of the well founded Austrian data basis. Other regions can, in general, easily be included in further investigations in the same manor.

3. Methodology and modelling framework

Artificial Neuronal Networks have successfully been used in a wide range of applications, for example in pattern recognition, classification and for regression problems. The problem stated here is a regression problem, but whereas normally a single output (i.e a single time-series) is modeled, this paper is focusing on multiple output time-series. It can be expected that a single output would result in better regression performance, since errors of all output variables are optimized combined in the ANN model. The major advantage of the proposed modeling approach is that cross-dependencies of output variables can be taken into account. Last year's outputs of all commodities and prices are used as an input for next year forecasts and iteratively prescribed in the future. In a linear model this would typically require a set of cross-elasticities for prices and quantities. For the type of time series problem stated here, the proposed approach is to predict future values of set of time series $y_A(t)$ from past values of that time series (commodities and commodity prices) and past values of set of second time series $x_B(t)$ (exogenous variables). This form of prediction is called nonlinear autoregressive with exogenous (external) input, or NARX, and can be written as follows:

$$y_i(t) = f(y_A(t-1), ..., y_A(t-d), x_B(t-1), ..., x_B(t-d)) \qquad | \, i \in A \qquad (1)$$

3.1. Artificial Neuronal Networks

The principal idea behind ANN is to train and evaluate simple interconnected processing units comprised of Neurons and Synapses, normally in the range of 5 to several hundred, according to how the brain performs. (The human brain has roughly 10^{11} Neurons and 10^{14} Synapses [13]). Neuronal Networks have been applied successfully to model complex function forms.

Each of the neurons calculates a weighted sum of its inputs (w), to which a constant bias (b) is added. This sum is then passed on to a transfer function, normally a linear, hyperbolic tangens or sigmoid function (others are possible but rarely used). Sigmoid transfer functions are widely used for regression problems [14]. The neurons are arranged on several layers and comprise the network architecture. Typically the input layer is only used to pass on the input variables. The processing of the data takes place in one or more "hidden layers" and the output layer. The ANN developed here uses a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer of the network.

4. Network design and experimental setup

In order to find the optimal network architecture, several combinations were evaluated. These combinations included networks with different numbers of hidden layers, different numbers of units in each layer and different types of transfer functions.

Good performance showed the matlab neuronal network toolbox with a recursive back-propagation network, a network delay of two time-steps (the previous two data points are used as input) and 10 hidden neurons. Figure 3 and 4 show the network architecture with an input layer comprising of 22 input variables (11 commodities and prices) plus 6 exogenous input variables, one hidden layer consisting of 10 neurons, and an output layer with 22 output variables.

Forecasting with neural networks involves two steps: training and learning. The training set is given by the historical data, containing both inputs and the corresponding desired outputs, which is fed into the network. In the learning process a neural network constructs an input-output relation, adjusting the weights and biases at each iteration based on the minimization of an error measure (commonly mean square error) between the output produced and the desired output. Thus, neuronal network learning is an optimization process. The inputs to the neuronal network are normalized (on a 0 to 1 scale) in order to allow for an equal minimisation of the errors. (Otherwise time series with higher values would have a higher impact in the summed error term.) Several optimization criteria can be used. The error term for a single commodity is expressed as difference between predicted and actual value.

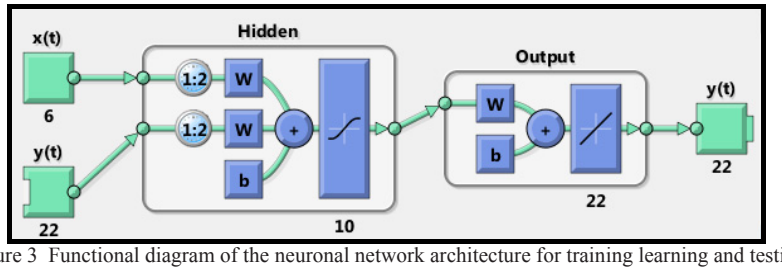

Figure 3 Functional diagram of the neuronal network architecture for training learning and testing

Summed Mean Square Errors (MSE) have resulted in better forecasting results compared to Summed absolute squared error in this model set up. MSE is most commonly used as optimization criterion in this field, however, other optimization criteria like the Noise to Signal Ratio or Normalized Mean Square Error [15] might result in even more accurate forecasts and should be considered in further research.

The error minimization process is repeated until an acceptable criterion for convergence is reached. The information acquired by the neural network through the learning process is tested by applying new data from the historical dataset, that it has not been used before, called the testing set (see figure 5). The network should be able to generalize and have an accurate output for this unseen data.

After the network has reached a satisfying performance on the testing set, the network loop between input and output variables is closed to allow for a several time steps ahead forecast, which is done on an iterative basis (see Figure 4).

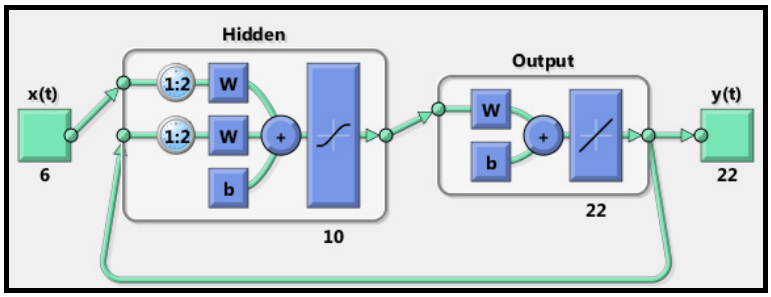

Figure 4 Functional diagram of the neuronal network architecture for testing and application

5. Results and conclusion

Due to the iterative weighting approach and the random divide of the data set in to training testing and validation set, a neuronal network with same initial criteria can result in different outcomes. In figure 5

the MSE of the ANN is shown after several iterations. It can be seen, that although the error for the training set decreases, the error for testing and validation increases. Therefore further training of the network after the 6th reiteration results in over-fitting of the network.

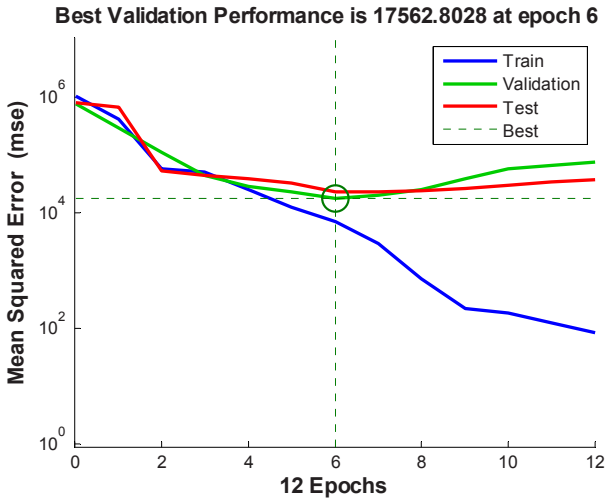

Figure 5 Performance of the neuronal network in testing, validation and training

Figure 6 shows exemplary that auto correlation is within the 95% confidence limit for the errors (er) of time series 1, in this case sawnwood demand. It is used to validate the network performance. It describes how the prediction errors are related in time. For a perfect prediction model, there should only be one nonzero value of the autocorrelation function, and it should occur at zero lag. (This is the mean square error.) This would mean that the prediction errors were completely uncorrelated with each other (only white noise). If there was significant correlation in the prediction errors, then it should be possible to improve the prediction. In this case, the correlations, except for the one at zero lag, fall approximately within the confidence limits, so the model seems to be adequate. The mean square error of the sawnwood time series amounts to approximately 5×10^4, compared to the total MSE of 17.563×10^4 of the model. Blue bars represent the correlation expressed as $E[(er_t-\mu_{err}) \times (er_{t+lag}-\mu_{err})]$, where E is the expected value operator.

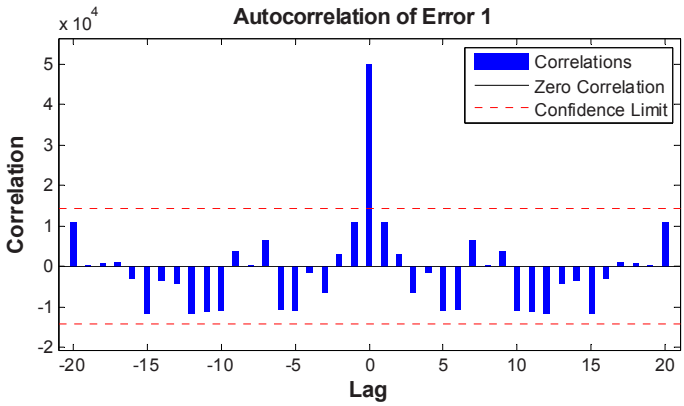

Figure 6 Auto Correlation of the error in the sawnwood demand time series

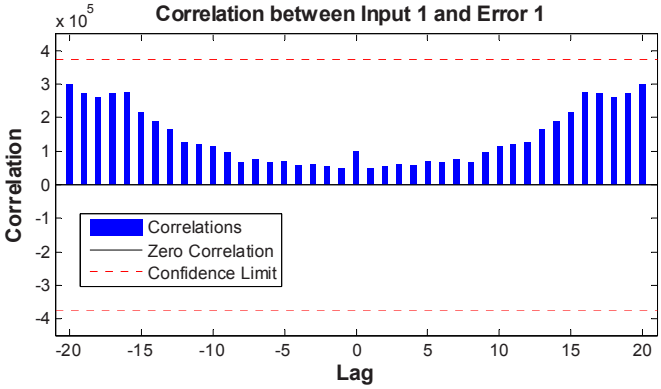

Figure 7 Input-error cross-correlaion

Figure 7 exemplary shows that Input-output error cross-correlation is within the 95% confidence limit. It shows how the errors are correlated with the input variables x(t). For a perfect prediction model, all of the correlations should be zero. If the input is correlated with the error, then it should be possible to improve the model. Blue bars represent the correlation expressed as $E[(Y_t-\mu_Y) \times (er_{t+lag}-\mu_{err})]$.

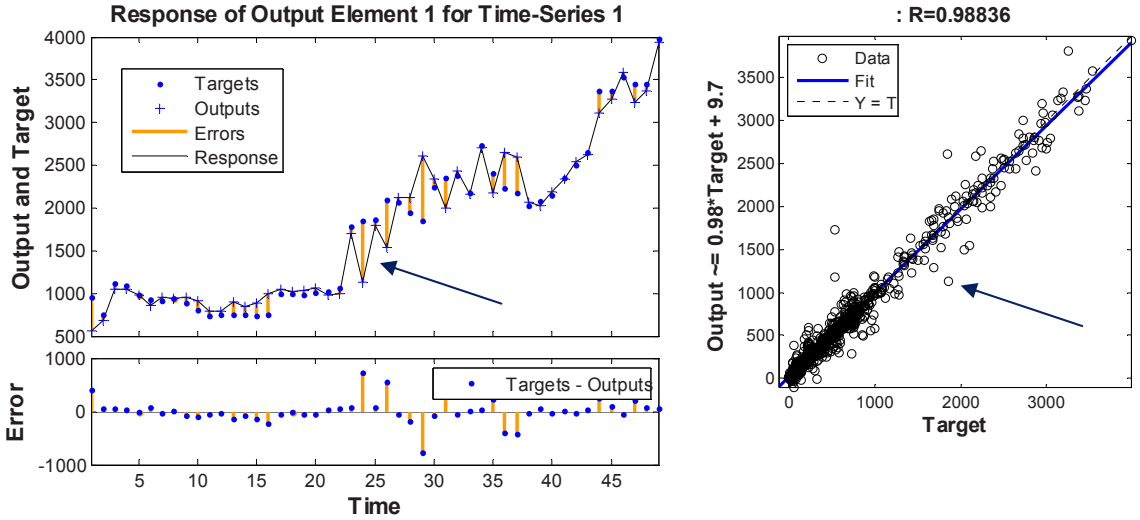

Figure 8 (a) Actual (target) and predicted (outputs) time-series for sawnwood consumption in Austria 1961-2011; (b) Input –output correlation for all commodities and prices

Figure 8 shows the time-series for sawnwood in Austria starting in 1961. Obviously, larger errors occur, starting in 1985 (T=24). These errors can also be observed in the overall input output correlation (marked with an arrow). In a preliminary test on all single commodities shown in Figure 1 separately, it could be shown, that neuronal networks were able to fit the input variables GDP per capita, population, world GDP better (with a higher correlation coefficient) in all cases when compared to linear regression.

For all variables combined, the neuronal network also performs very good (R=0,99) in terms of input output correlation in the actual model setup.

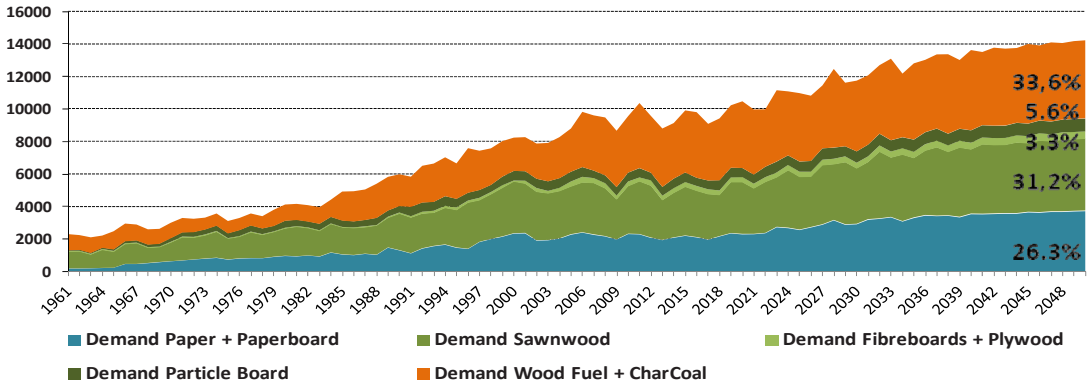

Figure 9 Forest commodity demand in Austria (1961-2050) in the high carbon scenario and shares of total demand in 2050

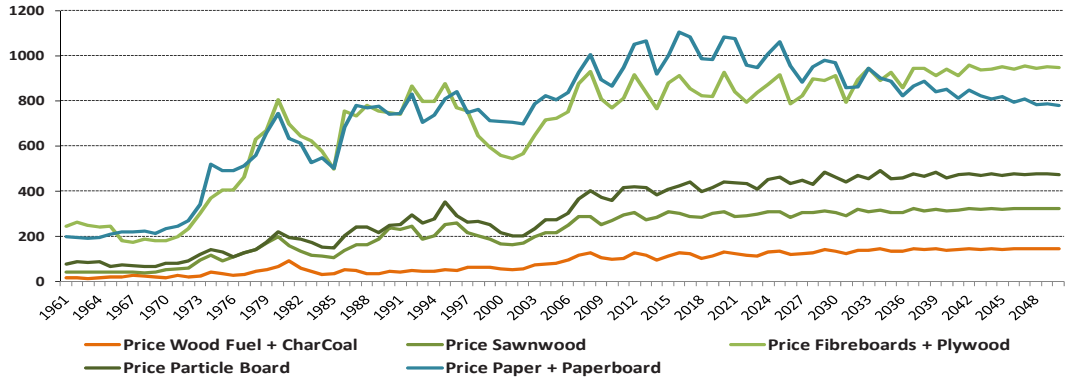

Figure 10 Prices of forest commodities in Austria (1961-2050) in the high carbon scenario

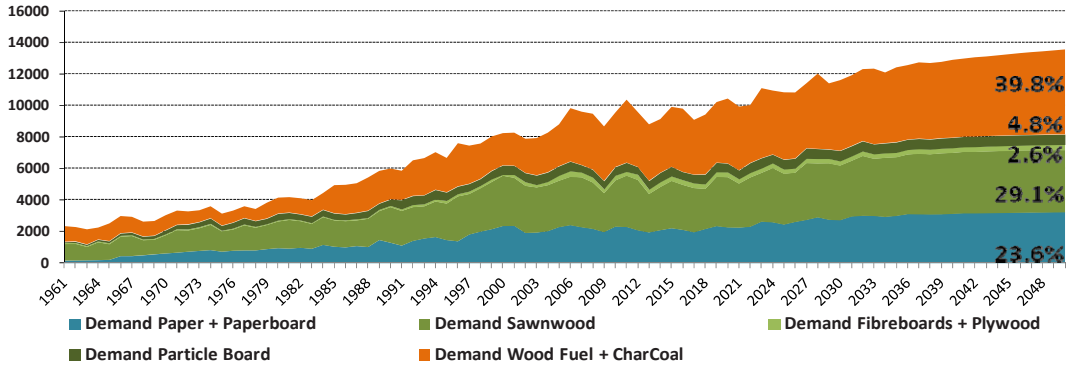

Figure 11 Forest commodity demand in Austria (1961-2050) in the low carbon scenario and shares of total demand in 2050

Figure 9-11 shows the output of the ANN for the high and low carbon scenario, aggregated in five commodities. Generally, it can be assumed, that more ambitious emission targets would result in a larger forest bioenergy demand. The low carbon scenario shows a minor decrease in overall forestry commodity demand and a decrease in the relative share of all commodities for material use, whereas biomass for energy is increasing. This result points to the conclusion that the functional relation between emission targets and biomass use can be captured by the model. Further, the expected negative relation between quantities and prices seems to be captured, but still remains to be proven.

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