# Effects of Moisture Content on Supply Costs and $CO_2$ Emissions for an Optimized Energy Wood Supply Network

**Christian Kanzian, Martin Kühmaier, Gernot Erber**

***Abstract***

*The supply of wood for energy is challenging due to high supply costs and rapidly increasing demand. As an important quality criterion, moisture content (MC) influences the revenues, demand and supply costs. For transport, the limiting factor is payload, if the MC is high.*

*The effects of MC on costs and greenhouse gas (GHG) emissions for an optimized supply network have been analyzed using a previously developed multi-criteria optimization model by using different MCs in the range from 50 to 20%. The weighted sum scalarization approach was used to derive Pareto optimal points by changing weights stepwise from maximum profit to minimal GHG on a relatively large scale network of 356 storage locations, 119 freight stations and 228 plants.*

*A decrease of 10% in MC from 40 to 30% will double the profit from 5.10 to 12.00 EUR × $t^{-1}$. In the case of MC independent revenues, the sensitivity of the model is lower but clearly visible, with a profit increase from 6.00 EUR × $t^{-1}$ at the MC of 40% to 10.00 EUR × $t^{-1}$ at the MC of 30%. As expected, emissions will decrease with a decreasing MC. However, the effect on emissions is less prominent than the effect on profit. Reducing MC from 40 to 30% will save approximately 4% of the GHG per dry t.*

*Keywords: supply network, moisture content, forest biomass, chips, transport, multi-objective optimization*

## 1. Introduction

The European Union (EU) has set an ambitious target for renewables to represent 20% of the overall energy supply by 2020 (EU, 2009). Based on the initial position of a country, various targets were set. In Austria, 34% of the energy in gross final consumption should originate from renewable sources by 2020. Limits for greenhouse gas (*GHG*) emissions were also set. Additionally, the Energy Efficiency Plan 2011 aims to decrease energy consumption by 20% by 2020 through increasing the energy efficiency at all stages of the energy supply chain (EU, 2012).

The replacement of fossil fuels by forest biomass should help to mitigate *GHG*. However, the supply of wood for energy is challenging due to high supply costs and rapidly increasing demand.

In contrast to other timber products, the quality of the product, expressed by a higher calorific value, can be increased through storage for the energy supply (Brand et al. 2011). During storage, natural drying reduces the moisture content (*MC*), which leads directly to a higher calorific value. However, depending on material type and weather conditions, different results have been obtained during precise measurement of natural drying (Erber et al. 2014; Routa et al. 2015). Supply and demand fluctuate between heating and non-heating season. To balance supply and demand and to enhance the fuel quality, storage of wood to be used for energy is preferable in most cases.

Suitable storage or terminal locations within a supply network for energy wood can be determined with different approaches, where mathematical optimization is often applied. Driven by the need to make it more economical, research started to focus on biomass supply over the last decade. The number of research papers dealing with biomass supply chain models is rising exponentially, with linear-, integer-, mixed integer-, and nonlinear programming, heuristics and multi-criteria decision analysis as common methods (Meyer et al., 2014). Examples of strategic supply chain optimization models can be found in Gunnarsson and Rönnqvist (2008), D'Amours et al. (2008) or Flisberg et al. (2012) and for operational optimization, such as truck routing and scheduling, in Flisberg et al. (2012), Hirsch (2011) or Oberscheider et al. (2013). Zamora-Cristales et al. (2015) used a simulation model to calculate costs for different supply chains on the pile level and used the results as input for a mixed integer optimization model to select the best supply options.

Of course, most of the optimization studies focus on economics. However, there is an increasing interest in optimization of supply chain sustainability, taking into account the three dimensions of economy, environment and social issues (Eskandarpour et al. 2015). Especially for the biomass supply, environmental impacts such as *GHGs* are of interest and need to be minimized.

The impact of moisture content on supply costs and emissions for an energy wood supply network has not been studied extensively. For example, Acuna et al. (2012) developed a multi-period optimization model to analyze the effect of *MC* on storage, chipping and transport for three different supply chains over a two-year period delivering forest energy to a single plant. Results show that proper storage and drying results in saving 33% of the harvested volume.

Sosa et al. (2015) applied a quite similar optimization model in an Irish case study. Interestingly, a constraining *MC* for delivered material led to higher costs compared to an unconstrained *MC* scenario due to the higher transport distance to gather only material with lower *MC*.

Changing moisture content has an impact on the whole supply chain. To investigate the effect of *MC* on supply costs and emissions for an energy supply network, the multi-objective mixed integer optimization model presented in Kanzian et al. (2013) was extended. The model considers two objectives: the first is to maximize the profit, and the second is to minimize $CO_2$ emissions. By employing the weighted sum scalarization approach (Ehrgott 2000), where the sum of two scaled objectives has to be minimized, Pareto optimal solutions for different weighting combinations were determined. Staying on the one hand within the forest resource limit and on the other hand fulfilling the demand is done by constraints. Using flow and capacity constraints for the terminals and shipping stations ensured that flow over terminals is kept within given limits. To reduce chipper movement and prevent transport capacity underutilization, forest resource points (road side storage) were either classified »material dedicated to chipping« or »material not dedicated to chipping«. Thus, splitting of a resource point material into two different transport forms was avoided. As case studies have shown, demand and resources do not always meet. Based on these experiences, three conditional model constraints were added to enhance the model robustness in the case of limited resources. A total of 90% of the resources should be allocated to demand points and at least 50% of each demand must be fulfilled. Detailed information on the model formulations is provided in Kanzian et al. (2013). For the study, the *MC* has been assumed to be constantly at an average of 37.5% at first. In a further setup, to figure out the sensitivity on the given supply network, different *MCs* will be added as additional model parameter. Different sensitivity analyses were carried out to determine and show the impact of this parameter.

## 2. Materials and methods

### 2.1 Supply chain assumptions

As in Kanzian et al. (2013), five different supply chains have been considered in the study (Fig. 1). Each chain starts at the forest road after harvesting. Depending on the chipping location, different types of materials need to be transported.

Supply chain 1 (SC 1): Energy wood is chipped directly at the forest road or landing and transported, chipped, to the plant by trucks.

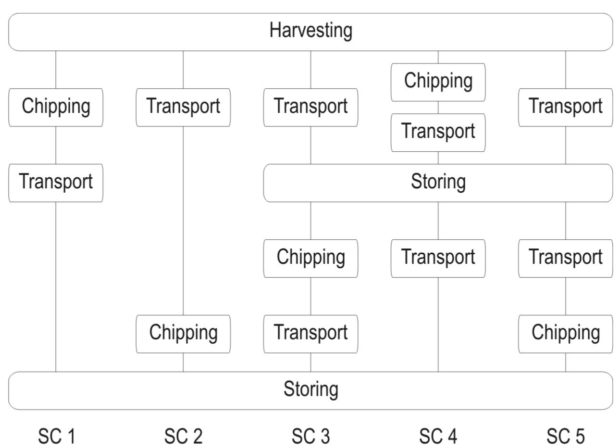


**Fig. 1** Supply chains considered in the optimization model

Supply chain 2 (SC 2): Log trucks transport unchipped material directly to the plant, where it is chipped.

Supply chain 3 (SC 3): Log trucks transport unchipped material to an intermediate storage area, where it is chipped directly onto trucks and then transported to the plant after seasoning.

Supply chain 4 (SC 4): Energy wood is chipped at the forest road and transported to and unloaded at an intermediate storage area. The chips are later loaded onto trucks again and transported to the plant.

Supply chain 5 (SC 5): Log trucks transport the unchipped material to a storage area for seasoning. After seasoning, log trucks transport the unchipped material to the plant for chipping.

Supply chain 5a (SC 5a): Log trucks transport the unchipped material to a shipping station and load the unchipped material onto wagons. The material is taken to the plant by railroad for chipping.

### 2.2 Mathematical model parameters and moisture content

To optimize the selected supply chains, the parameter calculation in the model code from Kanzian et al. (2013) was reworked to enable studying changes in *MC*. To enhance the model flexibility and facilitate studying the model sensitivity, cost and emission data calculations were implemented in the model code. The *MC* of the energy wood mainly influences demand, transport costs and revenues. The lower the *MC*, the lower the demand will be, due to the higher heating value of the wood. Furthermore, most pricing schemes for energy wood depend on the *MC* of the delivered material. The higher the *MC*, the lower the price will be.

The revenues at the plant for solid and chipped material originate from a tariff list of the biggest plant within the testing area, which considers the *MC* for pricing. Other pricing data were not available and thus, this list was assumed to be representative for the study area. Based on this list, using regression analysis, functions for predicting the revenue at a given *MC* have been generated (1–2).

$$r_{j,k=0} = 60.273 + 36.105MC - 99.415MC^2 \quad (1)$$

$$r_{j,k=1} = 81.346 + 30.558MC - 86.271MC^2 \quad (2)$$

Road transport costs per entity ($c_{ijk}$) depend on time associated with transport, loading, unloading and operational delays. Time consumption for driving empty and loaded was assumed to be equal. Total transport time is multiplied by the hourly costs, and road charges are added. Finally, the costs for one trip are multiplied by the number of trips needed for completing the job and then divided by the volume per resource point to determine the costs per entity (3). The number of trips ($n_{ik}$) was determined by dividing the volume per resource point and the payload ($lv_k$). This number was then rounded up to the next integer, as there is always one truck trip needed, regardless of the amount transported (4).

$$c_{ijk} = \frac{\left((t_k^L + 2t^D + t^U + 2p_k^W + t_k^D)c_k^h + 2c_{ij}^{toll}\right)n_{ik}}{s_i} \quad (3)$$

$$n_{ik} = \frac{s_i}{lv_k} \quad (4)$$

The transport capacity of trucks and wagons is limited by either maximum payload (tons) or volume ($m^3$). Load limits for the truck and trailer used in the analysis can be found in Table 2. To determine the maximum payload at a given *MC*, a simple routine was devised for checking whether the payload or the volume was the limiting value. The conversion factor from $m^3$ loose to dry ton was set at 5.26 based on an average wood density of 475 kg $m^{-3}$ and a bulking factor of 2.5 from solid to chipped wood.

Time consumption for different working steps was obtained from our own studies (Holzleitner et al. 2011, 2013). The shortest drive times between the network nodes were calculated in a GIS and stored in a geodatabase. Unluckily, for $CO_2$ emissions we do not have such detailed analysis of different work phases, and we needed to fall back on distance-based emission calculations, using average values of fuel consumption per km.

The transport cost by rail for timber freight cars was derived by joining the tariff list scaled by distance and the shortest railroad distance from GIS analysis. Emissions for rail transport per distance and weight were taken from the database of the Global Emission Model for Integrated Systems (GEMIS) and apportioned to the transported energy wood.

### 2.3 Test case

For testing purposes, we used the same project area as was chosen in Kanzian et al. (2013). This project area has a total size of 47,200 $km^2$ and is split into 38 forest administrative districts (FADs). Gronalt and Rauch (2008) estimated the total available volume of energy wood for these districts to be 882,170 oven dry tons (t). A square grid of 1.5 by 1.5 kilometers, laid over the forest area and resulting in 9,984 possible resource points, represents the resources. Depending on the forest area and the resources of each FAD, between 31 and 518 points with a single resource volume between 32.7 and 139.9 t × a$^{-1}$ were generated.

The number of heating plants across the study area increased over the last two decades, so we selected a total of 228 heating and combined heating plants with a heating capacity of more than one MW per plant by merging the data provided by different provinces. Smaller plants with a heating capacity lower than one MW were excluded, as their catchment area was assumed to be too small for our chosen scale.

The total energy wood consumption of the selected plants is 982,000 t × a$^{-1}$, which exceeds the forest resource potential of the supply region. The energy wood demand is not uniformly distributed because larger heating plants with a demand of more than 20,000 t × a$^{-1}$ are mainly located in the east and north, close to the borders of the study area (Fig. 2).

A survey of 72 plants performed in 2010 discovered an average MC of 36.8% for the energy wood delivered. A clear and significant trend was detected showing that larger plants take fuel wood with a higher *MC* (Matzinger 2010). Using the prediction of Matzinger (2010), the average *MC* for the test case was set to 37.5%. As the *MC* influences the heating value, the demand in dry t was also assumed to change. Based on the actual *MC*, the demand was adjusted by its heating value, using the average *MC* as the reference value.

A GIS procedure helped to find possible storage and terminal sides, respectively (Kühmaier et al. 2014). Due to the risk of bark beetle infestation in coniferous stands in Austria, storing of softwood for longer periods should be avoided in spring and summer. For different criteria, such as distance to settlements or coniferous forests, the public road network and a minimum slope, grid layers were calculated in GIS (Kühmaier et al. 2014). Areas suitable for terminals were generated by weighting and combining these layers. Within these areas, terminal points with a ten km radius each were located, totaling 356 terminals (Fig. 2). Equipped with a 60 cm thick gravel layer and an expected lifetime of ten years, fixed cost for these terminals amounted to 1,100 EUR × a$^{-1}$. Variable costs per t depended on the

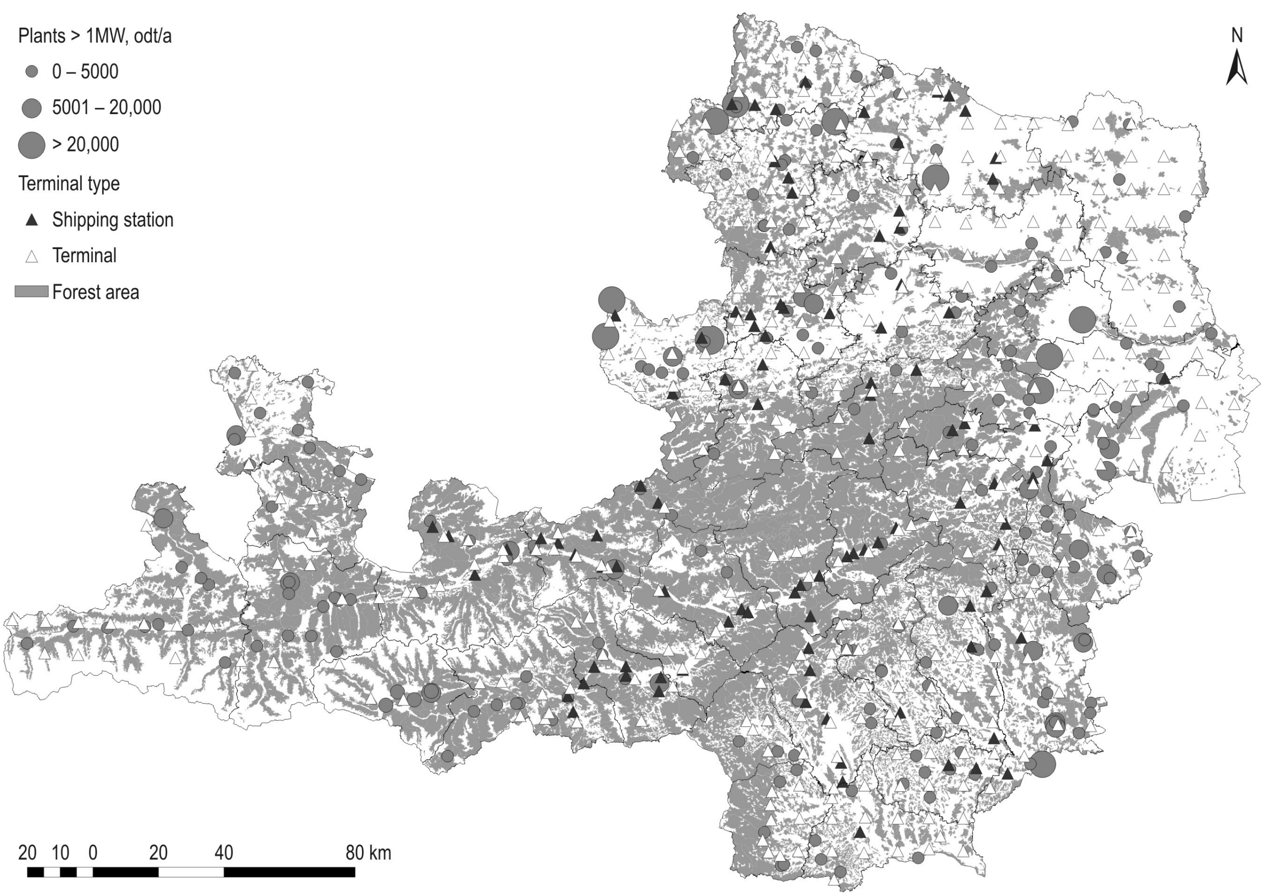


**Fig. 2** Study area with 38 forest administrative districts, forest land cover, locations of heating plants categorized into three sizes, terminal locations for storage and shipping stations for railway transport (Kanzian et al. 2013)

**Table 1** Indices, decision and data variables used within the multi-objective optimization model

| + | Description |
|---|---|
| | Sets |
| P | Set of forest resource points (roadside stocks) |
| L | Set of terminals |
| S | Set of shipping stations |
| H | Set of plants |
| K | Transport mode – (0) solid or (1) chipped |
| | Parameters |
| $s_i$ | Volume of energy wood at *i*; |
| $r_{jk}$ | Revenue at *j* for fuel type *k*, $j \in H; k \in K$ |
| $c_{ijk}$ | Transport costs from i to j for fuel type k, $i \in P \cup L \cup I;\ j \in H \cup L;\ k \in K$ |
| | Variables |
| $x_{ijk}$ | Volume to be transported from i to j at mode k, $i \in P \cup T \cup S;\ j \in T \cup S \cup H;\ k \in K$ |

type of energy wood (solid or chipped) and ranged between 10.4 and 9.5 EUR × $t^{-1}$. Emissions for the terminal construction were estimated to be 90 kg $CO_2$ × $a^{-1}$ and 0.45 kg $CO_2$ × $t^{-1}$ per t transferred via terminals (Kanzian et al. 2013).

### 2.4 Model implementation

A commercial solver platform (XpressMP, Fair Isaac Cooperation) was chosen for the implementation of the optimization model. Input and output data were stored and managed within personal databases partly using SQL queries. Origin destination matrices were calculated in a GIS using network analysis extensions. Output data were analyzed with the statistical software *R* (*R* Development Core Team 2014) and the packages RODBC (Ripley and Lapsley 2015), reshape2 (Wickham and Hadley 2007) and plotrix (Lemon 2006).

## 3. Results and discussion

### 3.1 Pareto analysis and moisture content sensibility

Supposing that the Pareto optimal solutions follow the convexity assumption (Ehrgott 2000), a finite number of combinations was selected to generate Pareto curves for decision makers. Weighting values for profit ($\lambda_p$) and emissions ($\lambda_e$) were set in a range from 0 to 1 with an increment of 0.5 and 0.1, respectively. By plotting the results for each model run, the Pareto curve provides a starting point for interpretation. As

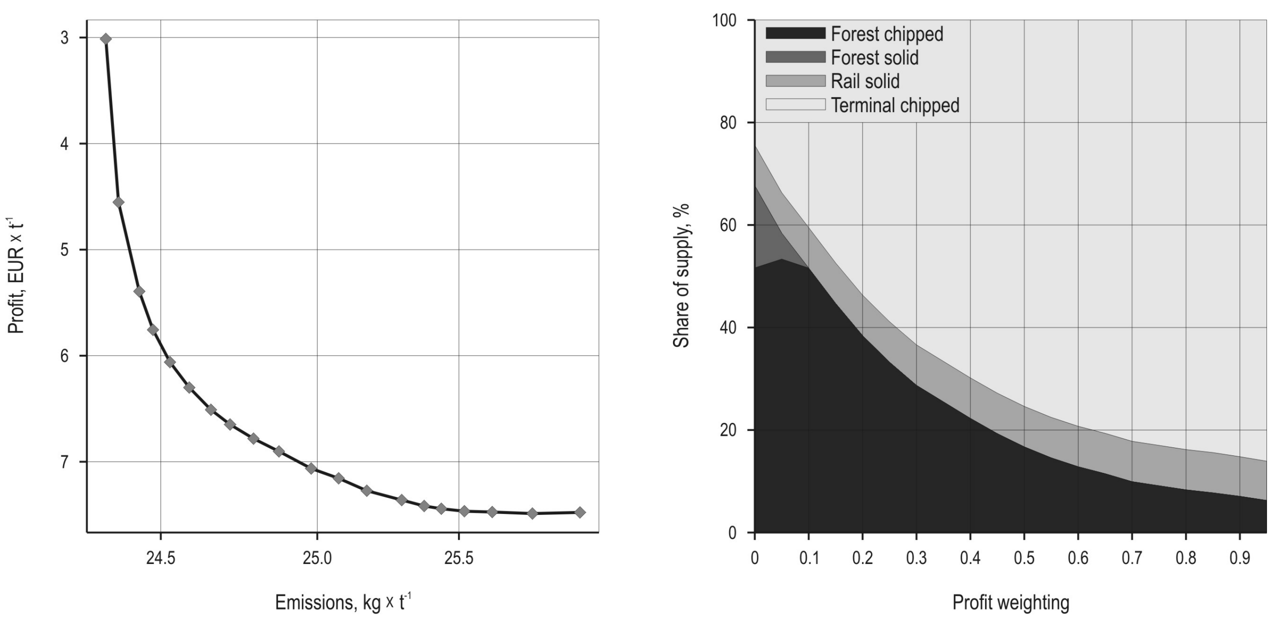


**Fig. 3** The result of 20 model runs with changing weights from 0 to 1 in steps of 0.05, showing the trade-offs between profit and GHG emission, was a typical Pareto curve (left). The share of energy wood supplied to the plants split into solid or chipped and its origin depending on the weighting between profit and emissions (right). A profit weight of 0 results in a minimum of emissions, whereas a weight of 1 results in a maximum of profit (Kanzian et al. 2013)

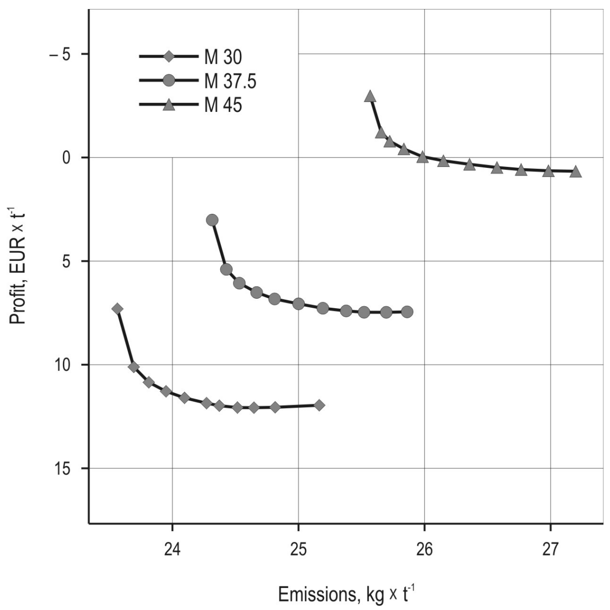


**Fig. 4** Pareto curves for different levels of moisture content

shown by Kanzian et al. (2013), to minimize the *GHG* emissions, 30% of the woody biomass should be delivered chipped from the terminals and more than 50% should be chipped directly from forest (Fig. 3, right), which causes emissions of 24.3 kg $CO_2 \times t^{-1}$ and results in gaining a profit of 3.0 EUR$\times t^{-1}$ (Fig. 3, left). The rest has to be delivered as solid energy wood directly from forest to plant. To maximize the profit by changing the weight, *GHG* emissions will only rise by 4.5%, whereas the profit more than doubles from 3.0 to 7.4 EUR$\times t^{-1}$. Thereafter, close to 90% have to be supplied chipped at the terminal because transport of chips is cheaper than transport of solid energy wood by log trucks. Furthermore, chipping costs at the terminal or storage place were estimated to be lower than costs of chipping at the forest roadside. Collecting energy wood at terminals will increase the transport distance and therefore increase *GHG* emissions under the given assumptions (Fig. 3, right). Actually, the legal gross vehicle weight limit is 42 t for log trucks and 40 t for chip trucks. If the values for both trucks were harmonized and set to 42 t, transport of chipped material would be cheaper, and the share would increase even more (Kanzian et al. 2013).

Using weights from 0 to 1 in steps of 0.1 for profit and emissions and three different *MC* levels of 30, 37.5 and 45%, the resulting Pareto curves are shifted as expected. Higher *MC* induces less profit and higher overall emissions (Fig. 4). In general, the profit is very sensible to changes in *MC*. At equal weights for profit and emissions, the profit will be close to 0 EUR$\times t^{-1}$ at emissions of 26.15 kg CO2$\times t^{-1}$ at the highest *MC* of 45%. If the *MC* drops from 45% to 37.5%, the increase in profit will be 6.80 EUR$\times t^{-1}$ and hence higher than during a further *MC* drop from 37.5% to 30% (4.80 EUR$\times t^{-1}$).

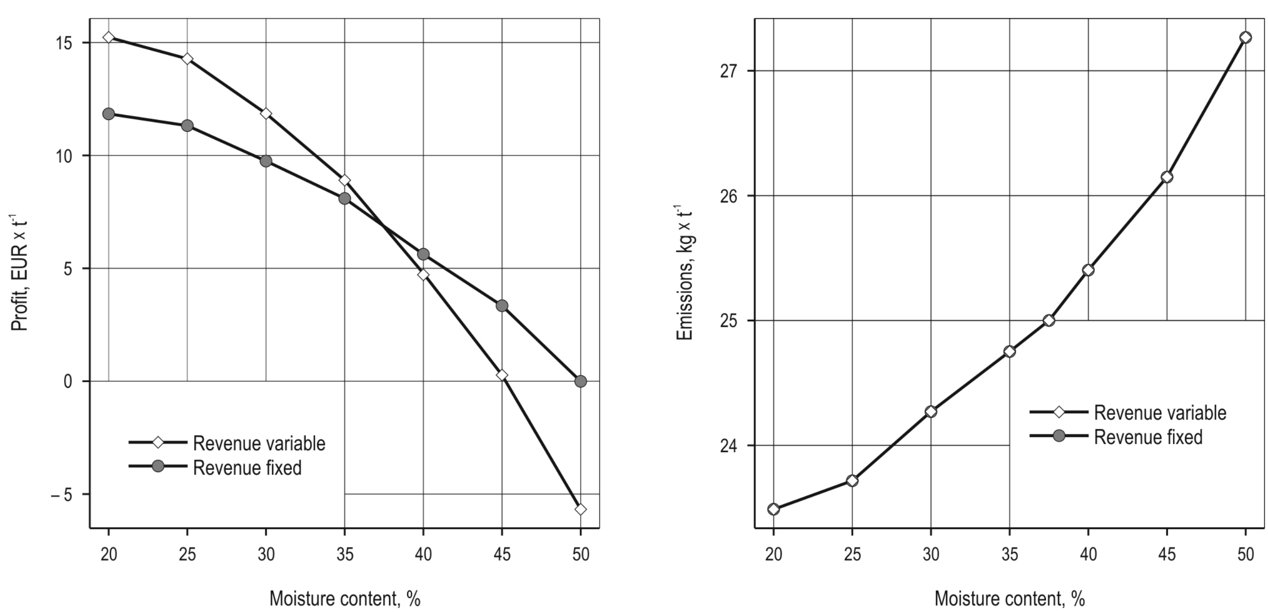


**Fig. 5** Sensitivity analysis of profit (left) and $CO_2$ emissions (right) on changing moisture content for two different revenue scenarios. In the first scenario – business as usual – the revenue is based on moisture content, whereas in the second scenario, the revenue is constant/fixed for an average moisture content of 37.5%

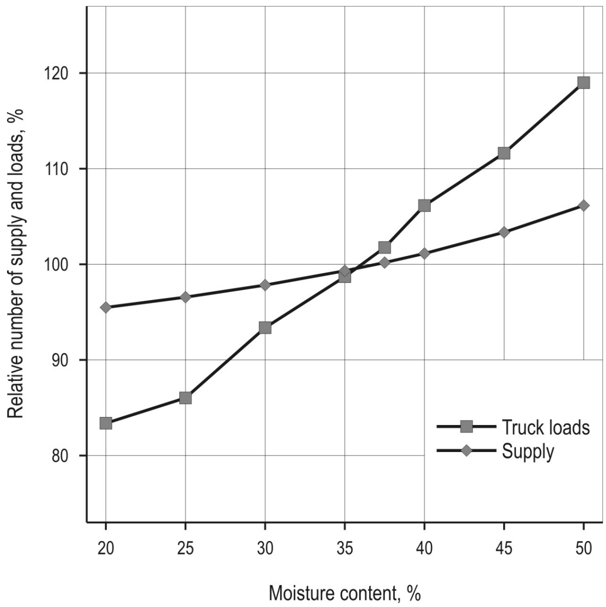


**Fig. 6** Sensitivity of supplied energy wood and number of truckloads needed to forward the energy wood at different *MC*s

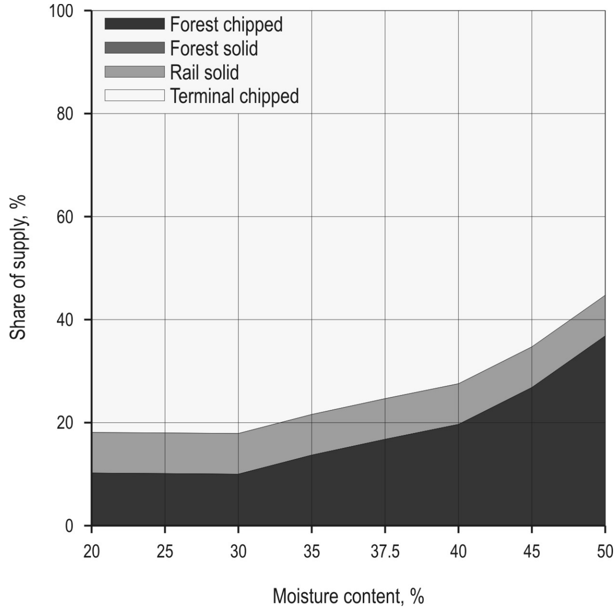


**Fig. 7** Share of supply sensitivity against changes in *MC* for equal profit and emission weighting value of 0.5

Of course, the profit is affected twice by the *MC* change, on one hand by the costs and on the other by the revenues. To rule out the effect of changing revenues and to show how transport costs are affected, another simulation with fixed revenues was conducted. In this case, the sensitivity of the model was lower but still clearly visible, with a profit increase from 6.00 EUR $\times$ $t^{-1}$ to 10.00 EUR $\times$ $t^{-1}$ by reducing MC from 40% to 30% (Fig. 5, left). With variable revenues, a decrease of 10% *MC* from 40 to 30% will double the profit from 5.10 to 12.00 EUR $\times$ $t^{-1}$. As expected, the emission will decrease with a decreasing *MC*, and there seems to be no dependence on the revenue. However, the effect of the decreasing *MC* is less prominent compared to the profit. Reducing *MC* from 40 to 30% will save approximately 4% of $CO_2$ emissions per t (Fig. 5, right).

Based on an average *MC* of 37.5%, the demand was adjusted before the optimization. For the test data, the supply decreased slightly if the *MC* was set to a lower value, but the change was small. Approximately 728,150 t would be supplied at 37.5% *MC*, while 2.2% less (711,020 t) will be supplied at 30% *MC* (Fig. 6). Of course, this slight change is caused by the soft constraints, which were added because of insufficient energy wood resources.

Considering the transport modes and how the material should be supplied, *MC* has an influence on the results. At the base *MC* level close to 17%, wood should be supplied chipped directly from the forest to the plants. The major share of 75% has to be delivered chipped via terminal. The amount of direct transport of chips decreases to 10% if the *MC* was set to 30%, whereby the delivery as chips via terminal increases to 82% (Fig. 7).

The average volume weighted road transport distances seem not to be very sensitive to different *MC*s

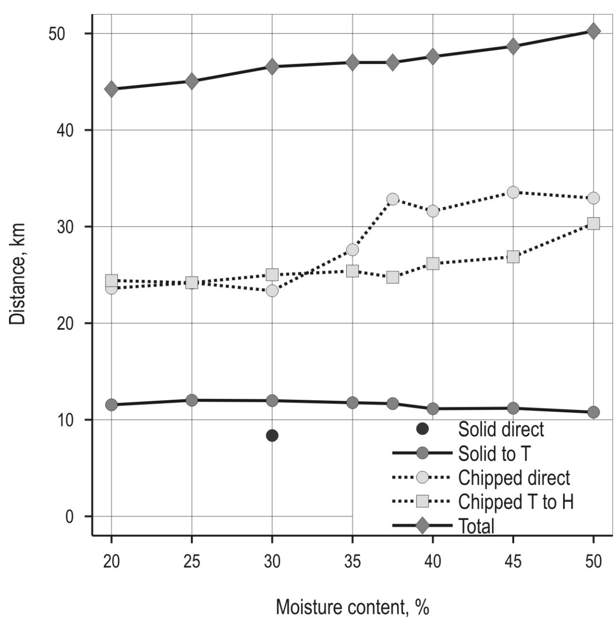


**Fig. 8** Average transport distances for solid and chipped material and its dependence on *MC* for equal profit and emission weighting values of 0.5

because the distance is more or less the same if an *MC* of 37.5% and 30% is tested at distances of 47.0 to 46.6 km. Of course, there is a relation between the share of supply and transport distances for different modes. The more material to be delivered chipped directly, which is the case at higher *MC*, the longer the transport distances of this mode (Fig. 8).

Increasing demand at higher *MC* results in a higher number of truckloads and a larger relative increase of truckloads than in actual supply (Fig. 6). There are 7% fewer truckloads needed to haul the energy wood at 30% *MC* compared to 37.5%, when the supply will be only 2.2% lower. For fresh material of 45 to 50% *MC*, the supply from the forests increases by 3.3% but requires 10% more truckloads.

Considering specific road transport distance and emissions per t, the effect of the *MC* becomes even more visible. The specific distance will decrease from 2.9 to 2.5 km $\times$ $t^{-1}$, if the *MC* is set to 30% instead of 37.5%. In addition, the specific emissions decrease from 0.33 to 0.27 kg $CO^2 \times t^{-1}$.

## 4. Conclusions

In this study, the multi-objective optimization model developed by the authors and presented in Kanzian et al. (2013) has been extended to study the impact of *MC* on profit and *GHG* for a supply network of energy wood.

Clearly, the *MC* has an influence on the efficiency of the whole supply chain network for several evaluation criteria. The weighted sum scalarization approach gives the possibility of including several objectives and to figure out the effects on profit and emissions quite quickly. Due to the nature of the study data, profit is more sensitive to changing *MC* than *GHG*. This result is less pronounced but still traceable via lower transport costs. *MC*-related revenues are excluded from the analysis.

Lower *MC* means reducing truckloads, which is beneficial both in terms of economy and environment. Interestingly, the specific emissions take more than proportional advantage of a lower *MC*. The effect of *MC* was expected to be more present, especially on the demand side and the transport distance, probably a result of the applied demand constraints that do not balance the demand.

Interestingly, fresh material with a high *MC* is more likely to be transported directly from forest to plant.

Currently the model considers only a period of one year and no change in *MC*. A further development into a multi-period optimization model opens up the possibility of considering a change in *MC*, e.g., by including the storage effect, estimated by natural drying models that have been developed and published recently.

**Table 2** List of parameters for transport cost calculations for solid and chipped material

| Definition, terms | Unit | Solid $k=0$ | Chipped $k=1$ |
|---|---|---|---|
| Loading time for mode *k*, $t_k^L$ | h | 0.8 | 1.08 |
| Driving time from i to j *k*, $t_{ijk}^D$ | h | GIS | |
| Unloading time *k*, $t_k^U$ | h | 0.53 | 0.62 |
| Waiting time as percentage of driving time, $p_k^W$ | % | 0 | 20 |
| Hourly costs *k*, $c_k^h$ | EUR$\times$h$^{-1}$ | 78 | 65 |
| Road charge from *i* to *j*, $c_{ij}^{tol}$ | EUR$\times$km$^{-1}$ | | |
| Load volume for mode *k*, $l_k^V$ | $m^3$ | 85 | 90 |
| Gross legal weight limit | t | 42 | 40 |
| Payload for mode *k* () | t | 22 | 22 |
| $CO_2$ conversion factor from l to kg | | 2.64 | |
| $CO_2$ emissions transport | kg $CO_2$ km$^{-1}$ | 2.05 | 1.32 |
| $CO_2$ emissions chipping | kg $CO_2$ t$^{-1}$ | 8.4 | |
| Conversion factor from loose $m^3$ to dry t | kg m$^{-3}$ | 5.26 | |
| Average wood density | – | 475 | |
| Conversion factor solid to loose $m^3$ | – | 2.5 | |
| Integer number of trips needed to transport the total volume from *i* for mode *k* ($n_{ik}$) | – | – | |

Transport costs are the driving force in fuel wood supply and need to be estimated as accurately as possible. In addition to *MC*, the bulk density plays an important role in determining the actual payload. The lower the bulk density of the raw material, especially the case for harvesting residues, the more likely is chipping in the forest to increase the density. Energy wood properties also affect chipper performance (Spinelli et al. 2011), which were assumed to be constant in the present study.

Although the results give a better understanding of the interactions between *MC* and energy wood sup-

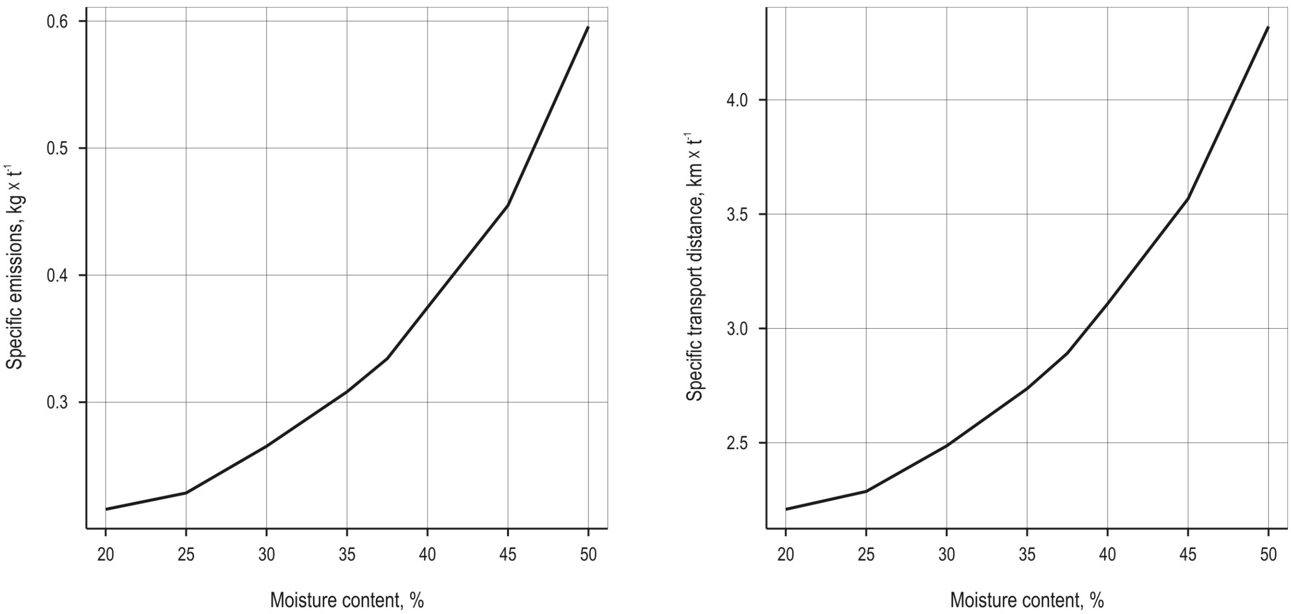


**Fig. 9** Specific emissions and transport distance per dry t depending on *MC*

ply network design, there are abundant possibilities for a further development of the optimization approach presented and a model to enhance the practicality and the decision quality.

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