INTEGRATING GOAL PROGRAMMING IN BIOMASS PROCUREMENT FOR BIO-ENERGY VALUE CHAINS

THAKUR UPADHYAY, REINO PULKKI*, CHANDER SHAHI, MATHEW LEITCH, AND BEDARUL ALAM

ABSTRACT

Goal programming was used to analyze biomass procurement value chains in the case of competing goals for power plants. One cost and six quality goals, namely moisture and ash contents and thermal values of each of two biomass types, were selected. Four model scenarios were investigated: i) benchmark total cost and upper bounds of the mean values of the six biomass properties (Initial Goals), ii) relaxing the quality goals by 10% from the Initial Goals scenario, iii) relaxing the quality goals by 20% from the Initial Goals scenario, and iv) all goals as in Initial Goals except that the Atikokan Generating Station (AGS) is supplied with only unutilized or underutilized biomass. Varying degrees of increase in total costs as well as costs for each power plant compared to the benchmark costs were observed for the other scenarios. The highest increase in total cost (7.54%) was observed for the scenario in which the AGS plant uses only unutilized or underutilized biomass.

INTRODUCTION

Use of bio-energy combined with other green energy sources such as hydro, wind, and solar power can contribute to reducing significantly our dependency on fossil fuels, thereby reducing greenhouse gas (GHG) emissions. Woody biomass is becoming more and more important as an alternative green energy source because it is available as a sustainable renewable resource and is CO\textsubscript{2}-neutral in terms of its production and consumption for energy purposes [1–3]. However, energy production from such woody biomass faces many challenges, including the uncertainty of biomass feedstock supply because of its sparse availability over space and time [1,4,5]. Furthermore, increasing demand for biomass feedstock for bio-energy production, as more biomass-based power plants come into operation, is causing a significant increase in transportation distances, leading to higher biomass procurement costs [6–8]. In this context, modelling biomass procurement cost structures under various resource constraints, competition, and various goals/targets for a group of power plants in the Canadian boreal region is of particular importance for understanding bio-energy value chains.

With the oil crisis in the 1970s and the consequent rapid rise in oil prices, there was much interest in Canada in biomass for bio-energy production, as demonstrated by the peak in research and development funding for the ENFOR (Energy from the Forest) program in the early 1980s [9]. However, with the ongoing decrease in oil prices from the mid-1980s until recently, research in biomass for bio-energy value chains was much reduced. In recent years, Canada’s degree of dependence on fossil fuels has changed, and forest biomass is again playing an important part in Canada’s energy consumption picture, supplying approximately 4.7% of primary energy demand and becoming the second-largest source of renewable energy after...
its power generating capacity is 230 MWe, forest biomass feedstock instead of coal. NWO, is currently being converted to use Station (AGS), another power plant in respectively. The Atikokan Generating and 61 MW th, and 30 MW e and 37 MW th will need to be used to meet the growing cies and unmerchantable standing trees in the future, currently underutilized spe- mainly of mill and logging residues, but small rural communities.

The biomass currently used consists mainly of mill and logging residues, but in the future, currently underutilized species and unmerchantable standing trees will need to be used to meet the growing demands for biomass. In this study, the entire forest-based biomass stream is classified into two sources: FHR, forest harvest residue, which includes tops, branches, and wood left after stand harvesting; and UUW, unutilized or underutilized wood, which includes currently unharvested tree species that are not commercially important for timber. There are numerous options for procuring forest biomass (terrain chipping/grinding, roadside chipping/grind- ing, terminal chipping/grinding, bundling, etc.) and several loading and trucking options. These biomass sources have various costs and properties and various potential impacts on other wood users (e.g., using standing trees for energy would compete with other wood users). Moreover, the biomass supply-chain conditions and demands change continuously throughout the year. The main challenge in supplying the four power plants with 2.21 million gt of biomass annually is at present to meet the demand while also meeting multiple targets in terms of the costs and properties of the feedstock.

Very few studies have been carried out on wood biomass for bioenergy sup- ply chains in Canada [13–16]. Most of the studies that exist focus on optimizing harvesting and transportation of raw material for the forest products industries from forest management units (FMUs) to the processing facilities. However, the authors found no studies relating to optimization of forest biomass feedstock supply from the forests to power plants for energy production, taking various costs and quality goals/targets into consideration, in NWO. The NWO study area is 167,184 km², with an annual average harvest of 60,867 ha (2002–2009), which is 0.61% of the productive forest area per year. The aim of this paper is to study how goal programming can be integrated into the wood biom- mass-for-bioenergy value chain in NWO given the presence of competing goals (four power plants competing for the given biomass feedstock, which has vari- able characteristics). Various sets of goals are analyzed, and the results are compared with those from a reference scenario consisting of a cost minimization problem in which other physical targets were not set, but were generated by a linear programming model (the benchmark LP model described in the Model Scenario section below). The goals or targets in the model are: minimize the procurement cost ($·gt⁻¹) of biomass; maximize the use of harvest residues and unutilized biomass; maximize the use of high-quality biomass with higher thermal value; and minimize the moisture and ash contents of the bio- mass feedstock. The variations in quality characteristics (thermal value, moisture content, and ash content) of the biomass distributed over the productive forest cells drive the results relating to cost structures with respect to different sets of goals or targets.

**METHOD AND DATA**

**Goal Programming Model**

In the past, multi-criteria decision-making (MCDM) models, which is a common name given to all relevant multi-objective decision model (MODM) techniques and other related simulation models, have been used to solve complex production and management problems in various natural resource management fields, including forestry [17,18]. The goal programming (GP) model, a variant of MODM, has been found to be particularly useful in production systems analysis because it can handle continuous problems involving the optimization of several simultaneous objectives [3]. The first GP model was reported in [19] and was developed to address the problem of infeasibilities caused by incompatible constraints. GP is an extension of linear programming (LP), which was developed to handle multiple, usually conflicting objectives in optimization problems. LP enables a firm to set the target levels of goals for various objects in a complex decision-making en- vironment. Unlike traditional LP models that deal with only one objective function to be either maximized or minimized subject to various resource constraints, GP
models are more relevant to analyzing the multiple objectives of an economic agent. References [20] and [21] represent a pioneering effort to criticize the traditional “rational economic man” approach with its single objective function of either maximizing profit/utility or minimizing costs, in which LP models can be used to solve such single-objective optimization problems. These researchers extended the rational agent model with its single objective function to multiple objectives with a “satisficing approach” in which the agent can have multiple objectives which form a hierarchy and in which the profit maximization/cost minimization issue may not arise. Problems structured using the satisficing approach are well handled by GP models.

The general specification of a typical GP model is:

Minimize \( Z = P + N \)  

Subject to  

\[ AX - P + N = G \]  

\[ BX \leq R \]  

\[ P+N = 0 \]  

\[ X \geq 0 \]  

where \( P \) and \( N \) are vectors of positive deviations (overachievement of the target or goal) and negative deviations (underachievement of the target or goal); \( A \) and \( B \) are matrices of technical coefficients relating to goal target levels and resource constraints respectively; \( R \) and \( G \) are vectors of resource stock/system requirements and targets/goals respectively; \( X \) is a vector of decision variables in the model with non-negativity constraints; and \( Z \) is a scalar sum of \( P \) and \( N \).

In this GP specification, there are no \( X \)s in the objective function (Eq. 1), and the objective functions are brought into the constraints with embedded positive and negative deviations, as shown in Eq. (2), which is also called a set of goal constraints. Equation 3 represents the resource and other technical constraints, and Eq. (4) restricts the model to choose either \( P \) or \( N \) for a given goal equation, but not both simultaneously. Furthermore, this standard GP model can be modified to minimize only \( P \), only \( N \), or both for a given objective function with certain goal(s).

### Study Area and Data

The study area, 324 km×516 km (167,184 km\(^2\)), consists of 18 forest management units (FMUs) and is located west of Lake Nipigon in NWO. Here, four power plants are currently operating with biomass as their feedstock. GIS data related to forest areas and depleted forest for the period from 2002 to 2009 were collected from Land Information Ontario Sustainable Forest Licence (SFL) holders and consulting firms in Shapefile and Geodatabase formats. The original vector data were first converted to raster format and finally to spatial database text files for the entire research area using ArcGIS software. Three main spatial layers (land use, forest depletion, and a cost layer) were prepared on a raster grid size of 1 km×1 km (1 km\(^2\)). This study examines 19,315 productive forest cells where timber harvesting activities occurred between 2002 and 2009 (forest depletion cells). The detailed methodology for estimating forest harvest residue and unutilized or underutilized biomass availability for all 19,315 forest depletion cells has been described in Alam et al. (2011). To estimate per-gt transport costs from each of the forest cells to each power plant, a road network layer was overlaid onto the forest maps, and the least-cost network was determined using a road network optimization algorithm as described in [22]. A fixed time for loading and unloading and a delay of 2.5 hours per trip are assumed to add CAD 4.85/gt to the variable hauling cost. Thermal values, moisture content (MC), and ash content for each type of wood biomass for each forest cell were estimated based on the results of studies reported in [23] and [24]. Other estimated techno-economic parameters used in the GP model are given in Table 1.

Descriptive statistics for the biomass properties were computed for all 19,315 forest depletion cells (Table 2). This step helped to determine initial target levels for each of the quality goals. Six quality-related goals were selected, namely the moisture and ash contents of both forest biomass types (four goals) and the thermal value of each forest biomass type (two goals).

<table>
<thead>
<tr>
<th>Description</th>
<th>Units</th>
<th>Estimate</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harvesting and processing costs (FHR)</td>
<td>CAD/gt</td>
<td>26</td>
<td>[11]</td>
</tr>
<tr>
<td>Harvesting and processing costs (UWW)</td>
<td>CAD/gt</td>
<td>31</td>
<td>[11]</td>
</tr>
<tr>
<td>Fixed cost due to loading/unloading overhead</td>
<td>CAD/gt</td>
<td>4.85</td>
<td>Authors’ estimate</td>
</tr>
<tr>
<td>Biomass demand of ABTB power plant</td>
<td>gt/y</td>
<td>730,000</td>
<td>Power plant data</td>
</tr>
<tr>
<td>Biomass demand of ABFF power plant</td>
<td>gt/y</td>
<td>800,000</td>
<td>Power plant data</td>
</tr>
<tr>
<td>Biomass demand of DDPP power plant</td>
<td>gt/y</td>
<td>480,000</td>
<td>Power plant data</td>
</tr>
<tr>
<td>Biomass demand of AGS power plant</td>
<td>gt/y</td>
<td>200,000</td>
<td>Power plant data</td>
</tr>
<tr>
<td>Harvesting factor*</td>
<td>% of BM</td>
<td>67</td>
<td>[2]</td>
</tr>
<tr>
<td>Number of forest depletion cells **</td>
<td>No</td>
<td>19,315</td>
<td>[22]</td>
</tr>
</tbody>
</table>

Note: CAD = Canadian dollars, BM = biomass, gt = green tonnes, y = year
*Percentage of the total amount of biomass that can be extracted from the given area.
**1km×1km harvesting sites in the forest area.
These goals provided a fairly good summary of biomass quality information to feed into the GP model. To estimate the values of all these parameters for the 19,315 forest depletion cells would be a daunting task, but estimated values of these variables at the FMU level give workable information.

**GP Model for Biomass Procurement**

The GP model is specified as minimizing the sum of positive and negative deviations from the target levels as appropriate, depending on the problem being studied.

The model proposed here minimizes the positive deviations of cost and heat values of FHR and UUW for each forest depletion cell and negative deviations of moisture and ash contents of the two types of biomass, FHR and UUW. The formal GP model is specified as follows:

\[
\text{Minimize } Z = p_1 + \sum_{j=1}^{19315} \sum_{i=1}^{4} (XBR_y (PR + TC_y)) + \sum_{j=1}^{19315} \sum_{i=1}^{4} (XBU_y (PU + TC_y)) - p1 \leq C \tag{6}
\]

where \( p1, p2j, \) and \( p3j \) represent the positive deviation of the total cost target (C) and the thermal value target of FHR (g_w) and UUW (g_w) for each forest depletion cell \( j \); \( n1j, n2j, n3j, \) and \( n4j \) are negative deviations from target/goal levels of the moisture contents of FHR (g_w) and UUW (g_w) and the ash contents of FHR (g_w) and UUW (g_w) for each forest depletion cell \( j \); PR is the processing (harvesting and grinding/chipping) cost ($·gt^{-1}) of FHR at roadside; PU is the processing (harvesting and grinding/chipping) cost ($·gt^{-1}) of UUW at roadside; DB_i is the annual forest biomass demand (gt) of power plant \( i \); ABR_j is the annual technical availability (gt) of FHR in forest depletion cell \( j \); ABU_j is the annual technical availability (gt) of UUW in forest depletion cell \( j \); TC_y is the biomass transportation cost ($·gt^{-1}) from the \( j \)th forest depletion cell to the \( i \)th power plant, including loading and unloading overhead; XBR_y is the amount of annual FHR harvested (gt) from the \( j \)th forest depletion cell for the \( i \)th power plant; XBU_y is the amount of annual UUW harvested (gt) from the \( j \)th forest depletion cell for the \( i \)th power plant; and XTB_i is the annual forest biomass (gt) brought into the \( i \)th power plant.

In this GP model specification, Eqs. (6–12) are the goal constraint equations, in which the scalars on the right-hand side are the chosen goal or target, each representing the decision-maker’s objectives which

### TABLE 2 Descriptive statistics of biomass quality variables and target levels by scenario (n=19,315).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Initial goals</th>
<th>10% relaxation</th>
<th>20% relaxation</th>
<th>UUWAGS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moisture Content FHR (% gw basis)</td>
<td>21.60</td>
<td>22.62</td>
<td>1.51</td>
<td>23</td>
<td>25.3</td>
<td>27.6</td>
<td>No FHR for AGS only, but the other plants are using it</td>
</tr>
<tr>
<td>Thermal Value FHR (GJ/ODt)</td>
<td>18.50</td>
<td>18.92</td>
<td>0.47</td>
<td>19</td>
<td>20.9</td>
<td>22.8</td>
<td></td>
</tr>
<tr>
<td>Ash Content FHR (%)</td>
<td>1.30</td>
<td>1.59</td>
<td>0.56</td>
<td>2</td>
<td>2.2</td>
<td>2.4</td>
<td></td>
</tr>
<tr>
<td>Moisture Content UUW (% gw basis)</td>
<td>22.50</td>
<td>29.77</td>
<td>4.13</td>
<td>30</td>
<td>33</td>
<td>36</td>
<td></td>
</tr>
<tr>
<td>Thermal Value UUW (GJ/ODt)</td>
<td>15.30</td>
<td>16.99</td>
<td>1.29</td>
<td>17</td>
<td>18.7</td>
<td>20.4</td>
<td></td>
</tr>
<tr>
<td>Ash Content UUW (%)</td>
<td>1.00</td>
<td>1.87</td>
<td>0.45</td>
<td>2</td>
<td>2</td>
<td>4.5</td>
<td></td>
</tr>
</tbody>
</table>

Note: FHR = Forest Harvest Residue, UUW = Unutilized or underutilized wood biomass, gw = green weight.
must be achieved through relevant deviations by selecting optimal values for the decision variables XBR and XBU. The cost target is determined based on the total cost obtained from the LP model without goal constraints with the same technical constraints as for the benchmark case. Different quality targets are selected based on the four goal-set scenarios described earlier. The Initial Goals scenario selects upper bounds for the mean values of each of the six biomass quality characteristics, as shown in Table 2. The constraints expressed in Eqs. (14) and (15) represent harvesting constraints and indicate that the annual harvest for each type of biomass should not exceed the available biomass in each forest depletion cell. Equation (16) requires that the total amount of forest biomass harvested for the ith power plant should at least meet the demand of that plant.

The complexity of this GP formulation can be seen in Eqs. (6–12), where the targets on the right-hand side are to be multiplied by the decision variables for each equation to cancel out the decision variables on the left-hand side so that resource characteristics described on the left-hand side become comparable with the goals (gi – g) on the right-hand side. This type of formulation is possible in the general algebraic modelling system (GAMS) programming language, and GAMS’s solver treats such a problem as a non-linear model. The solution procedure for the GP model selects the optimal forest depletion cells to harvest for FHR and UUW biomass to meet the annual feedstock requirements of each power plant while satisfying various cost and quality goals as discussed above. The moisture and ash contents of each type of biomass in forest depletion cell j can be underachieved because lower values of these properties are preferred, whereas the thermal values of each type of biomass in forest depletion cell j can be overachieved because a higher thermal value is preferred to a lower one. The hierarchical goal constraints of these biomass qualities will definitely increase total procurement costs, and therefore a positive deviation is allowed in the model.

**Model Scenario**

To test the various multiple-objective biomass procurement decision scenarios for the four power plants, four different goal-set scenarios were investigated. Before running the GP models, the benchmark LP model was run with a total cost minimization objective (sum of the costs for all four plants) with the usual constraints and without any quality targets (no target values set for moisture contents, thermal values, or ash contents). The results of the benchmark LP model gave an idea of cost goals and results as a basis for comparison of the biomass procurement costs for different scenarios in the GP model. Once the GP model as specified above starts to function consistently for these selected goal-set scenarios, it can then be used to run any combination of relevant goal sets, depending on the procurement managers’ criteria for goals and objectives.

The first scenario, Initial Goals, consists of a goal set in which the biomass properties (MC, ash contents, and thermal values) have upper bounds equal to the mean values of the corresponding variables (Table 2). This scenario is defined to establish baseline goals relating to biomass quality, where the power-plant manager may want to have higher-quality feedstock as defined by these threshold goals and targets. This goal set will introduce constraints into the model because the biomass to be harvested should have MC and ash contents not greater than the targets and the thermal value should be at least equal to the target. The second (10% Relaxation) and third (20% Relaxation) scenarios have goal sets that relax the target values for biomass properties (the target values are as shown in Table 2) from the Initial Goals scenario by 10% and 20% respectively. These two scenarios were run to test the sensitivity of the changes in goal levels (targets) to the cost structures of biomass procurement problems. The fourth scenario involved using only unutilized or underutilized biomass for the AGS power plant (the UUWAGS scenario) because this plant is planning to use UUW to produce pellets for power production in the future. Due to the strict ash-content requirements (<1% ash) of these high-quality pellets, only unutilized or underutilized biomass can be used for this purpose because logging residues would result in excessive bark and therefore too-high ash content. In this scenario, the other quality goals remain the same as in the Initial Goals scenario.

**RESULTS AND DISCUSSION**

The results of the benchmark LP model provide an optimal solution for supplying forest biomass feedstock from forest depletion cells in the case study area (19,315 forest depletion cells in the model with parameter values as shown in Table 1) to the four power plants by minimizing the total annual harvesting, processing, and transportation costs of biomass subject to the availability of forest biomass in each depleted forest cell, while meeting the biomass demand of each power plant.

The Dryden CHP plant is located near the middle of the research area, and there are many forest cells closer to this power plant than to others, along with a denser network of higher-class and straighter roads; all these factors imply a lower per-gt procurement cost for the Dryden plant (Fig. 1). Similarly, the AbitibiBowater Thunder Bay CHP plant is located in the southeastern part of the research area, with no competing power plant on its northern, eastern, and southern sides in the research area. The other two power plants (ABFF and AGS), which are located close to each other in the research area, must compete more strongly for forest biomass. Figure 1 shows the network of forest cells selected to harvest FHR and UUW biomass for the four power plants in the benchmark scenario. The model selects 11,790 and 2,991 forest depletion cells for supplying FHR and UUW respectively. The number of cells selected for FHR is greater because of its lower per-gt procurement cost compared to UUW (FHR is full-tree logging
residue material already at roadside). First, the model selects nearby forest cells (FHR biomass is preferred to UUW in a given cell because of its lower cost) to meet the power plant’s biomass demand; then it reaches farther away as more biomass is required. The issue of competition among the power plants for forest biomass is well captured by this model because the objective is to minimize the combined total costs of procurement, and it therefore becomes the rational choice to send the biomass from any given set of forest cells to the least-cost plant. The total cost derived from this model is used as the target or goal cost for the other four goal-set scenarios described below.

Table 3 presents the distribution of per-gt cost structures for the various goal-set scenarios over the power plants. The per-unit cost in each scenario can be compared with that of the benchmark as well as with the costs of the other three goal-set scenarios with respect to the Initial Goals scenario. It is apparent from Table 3 that per-gt procurement costs increase in all GP scenarios over those of the benchmark. Interestingly, the 10% and 20% Relaxation scenarios have lower per-gt costs than the Initial Goals scenario because these scenarios have lower constraints on quality and therefore allow more biomass to be collected. A convergence trend towards the benchmark costs as the targets on biomass qualities are relaxed is also evident.

Results for the last scenario, UUWAGS, suggest that when the goal of the plant manager is simply to procure

Fig. 1 - Optimal harvest of FHR and UUW biomass for the four power plants as determined by the benchmark LP model. Note: Forest harvest residue (FHR) is the left-over biomass after timber harvest, and unutilized or underutilized wood (UUW) is unmerchantable biomass, especially of hardwood species.
hardwood biomass for better-quality pellet production, the Atikokan plant has to pay more per gt, and at the same time other competing plants can grab the low-cost FHR biomass previously used by AGS, thereby reducing their unit procurement costs (compare the costs with those of the Initial Goals scenario in Table 3). These results are interesting and useful for power-plant managers who wish to judge the effect of trade-offs between quality and costs, as well as the cost impacts of the strategies of other competing plants. In addition to the four goal-set scenarios, a fifth goal-set scenario was also tried in the GP model, but the model solution was infeasible. The goal set in this scenario was to procure only FHR for all power plants under the quality goals from the Initial Goals scenario; this restriction caused the total availability of FHR biomass to be less than the total demand of the power plants. These GP model scenarios produce different distributions of optimal forest depletion cells for harvesting both types of biomass for each power plant (similar to that shown in Fig. 1), and the optimal distribution structure of forest cells changes in each scenario. Here, only the cost estimates for the model scenarios are presented in this discussion because the information required to determine a set of optimal forest cells for each scenario and each power plant is so huge that space does not permit a discussion. A database has been created containing the optimal set of forest depletion cells (from forest cell j to plant i) for each run of the model scenario. The changes in the optimal combination of forest depletion cells, which have logical implications for increasing or decreasing the total or unit costs of biomass procurement for each power plant and each model scenario, are well reflected in the cost information discussed below.

Table 4 contains the relative changes (in percentage terms) in total biomass procurement costs for each power plant under each model scenario. Here again, relative changes in costs can be compared to the benchmark and to the other GP model scenarios as well as to the Initial Goals scenario with respect to the other GP model scenarios (see the two sections of Table 4). The Initial Goals scenario is a base scenario for the GP model, and the other scenarios in this model are based on varying the parameter values from the base case, i.e., the Initial Goals scenario. This is why it is relevant to compare the results of the three GP scenarios with the Initial Goals scenario. The highest increase in cost compared to the benchmark cost from the Initial Goals setting was seen in the ATB plant, followed by AGS, ABFF, and DDPP in descending order.

The reasons for these variations basically involve the interplay of two factors: location of the power plants in relation to biomass availability in the nearby forest cells, and the size of their demand. The AGS plant has the lowest demand, but still faces the second-highest increase in cost due to the lower availability of high-quality biomass in its vicinity and the issue of competition with the ABFF plant. The results of the scenarios involving 10% Relaxation and 20% Relaxation in biomass properties show a smaller increase in costs for each plant, and with 20% Relaxation, the direction of change converges towards the benchmark costs. This occurs because as the quality constraints are relaxed, more biomass becomes available, and the problem tends to mimic the GP solution; this phenomenon also validates the model results. The UUWAGS scenario produced the highest increase in cost for the AGS plant (11.17%, see the fifth column of Table 4) because of the goal of harvesting only UUW biomass, which entails higher processing costs. The interplant externality of this goal can be seen in the slight reduction of cost for the other plants compared to the Initial Goals scenario (eighth column of Table 4).

The second part of Table 4 (starting from the sixth column) shows the relative changes in costs with respect to the Initial Goals scenario (the base scenario of the GP model). The results of the 10% Relaxation and 20% Relaxation scenarios in this case show significant reductions in costs compared to the Initial Goals scenario. Only the AGS power plant under the UUWAGS scenario shows an increase of 3.69% in cost from the base scenario of the GP model; the reason for this has already been explained above.

The results in Table 4 for relative changes in costs can be summarized in terms of the impacts of the goal-set scenarios and the distribution effect of each particular scenario in terms of cost structures among the power plants. One can also observe the impacts of goal-set

<table>
<thead>
<tr>
<th>Power plant</th>
<th>Benchmark</th>
<th>Initial Goals</th>
<th>10% Relaxation</th>
<th>20% Relaxation</th>
<th>UUWAGS</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABTB</td>
<td>38.11</td>
<td>41.84</td>
<td>39.24</td>
<td>38.29</td>
<td>41.82</td>
</tr>
<tr>
<td>ABFF</td>
<td>38.77</td>
<td>41.25</td>
<td>40.04</td>
<td>39.24</td>
<td>41.04</td>
</tr>
<tr>
<td>AGS</td>
<td>35.74</td>
<td>38.32</td>
<td>36.78</td>
<td>36.19</td>
<td>39.73</td>
</tr>
<tr>
<td>DDPP</td>
<td>36.13</td>
<td>38.15</td>
<td>36.70</td>
<td>36.27</td>
<td>38.13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Power plant</th>
<th>Percentage change from benchmark costs</th>
<th>Percentage change from Initial Goals cost scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Initial Goals</td>
<td>10% Relaxation</td>
</tr>
<tr>
<td>ABTB</td>
<td>9.77%</td>
<td>2.95%</td>
</tr>
<tr>
<td>ABFF</td>
<td>6.41%</td>
<td>3.28%</td>
</tr>
<tr>
<td>AGS</td>
<td>7.22%</td>
<td>2.91%</td>
</tr>
<tr>
<td>DDPP</td>
<td>5.60%</td>
<td>1.56%</td>
</tr>
</tbody>
</table>
scenarios on the total costs of biomass procurement under each scenario, as depicted in Fig. 2. The highest total cost is associated with the UUWAGS scenario because of the use of only high-cost UUW biomass by the AGS plant, which impacted the total cost as well. The positive deviations from the benchmark cost due to the introduction of goal sets in each scenario are plotted in Fig. 2 and show the difference between actual total cost and the benchmark total cost for each scenario. The lowest total cost and hence the lowest deviation from the benchmark total cost is associated with the 20% Relaxation scenario because of the greater relaxation of biomass quality goals relative to the base scenario. The relative increases in total costs compared to the benchmark case are 7.43%, 2.78%, 0.79%, and 7.54% respectively for the Initial Goals, 10% Relaxation, 20% Relaxation, and UUWAGS scenarios. However, the relative changes in cost for individual power plants compared to the benchmark costs vary over different scenarios from these total changes; this variation results from distributional effects which can be explained by resource availability and competition factors.

Due to the introduction of quality goals in the model, the total cost has increased from the cost obtained from the benchmark LP model. The quality goals/targets introduce constraints into the model and hence increase costs relative to the LP model because the total biomass requirement and operating efficiency for each power plant remain unchanged for all the GP scenarios while quality demands increase. Furthermore, this GP model can be extended to account for the impacts of higher-quality biomass goals on procurement and operating cost structures as engineering equations for conversion efficiency in relation to biomass quality are developed. In general, an improvement in efficiency for CHP and power-only plants would be expected with the use of higher-quality biomass (as discussed in this study), and therefore reduced total wood biomass costs in the value chain for a given amount of energy would also be expected, even though the delivery cost may be higher because of the goals requiring higher biomass quality. This trade-off between quality and costs can be modelled. The total biomass demand for each power plant becomes endogenous once the engineering process equations for biomass quality versus conversion efficiency for each type of power plant have been introduced into the model. Development of these equations is a topic for future work.

**SUMMARY AND CONCLUSIONS**

Biomass procurement problems for four bio-energy power plants in NWO that require approximately 2.21 million green tonnes (gt) of biomass annually have been analyzed using GP models. The biomass currently used is mainly mill and logging residues, but in the future, underutilized species and unmerchantable standing trees will need to be used to meet the growing demands for biomass. All biomass sources have variable costs, qualities, and potential impact on other wood users (e.g., using standing trees for energy would compete with other wood users). Moreover, the conditions and requirements in the biomass supply chain change continuously throughout the year. The multiple goals selected to address this problem are procurement cost plus several biomass quality properties. Six quality goals were selected: moisture and ash contents and thermal values for both forest biomass types. These provide a fairly good summary of biomass quality information to feed into the GP model. After the costs and the physical quality goals had been determined, four different scenarios were investigated, Initial Goals, 10% Relaxation, 20% Relaxation, and UUWAGS, and the results were compared with a benchmark LP cost minimization model with the usual constraints plus goal constraints.

The results of the model scenarios were compared with the benchmark as well as with the costs of the other three goal-set scenarios with respect to the Initial Goals scenario. The impact of the goal-set scenarios on biomass procurement costs was to increase these costs, in total as well as for each power plant, to varying degrees compared to the benchmark costs. The impacts of changing goals were interdependent between plants; changing a goal in one plant affects costs at other plants. With relaxation of quality targets or goals, the solutions showed a trend to converge towards the benchmark costs. The highest increase in total cost was found in the scenario in which the AGS plant used only unutilized or underutilized biomass. These results from the GP models could be useful for power-plant managers to judge the trade-offs between biomass properties and costs, as well as the impacts on costs of the strategies of other competing plants.
The successful development and use of GP models as described in this study confirms that use of such a model to analyze any combination of relevant goal sets depending upon the procurement managers’ goal/objective criteria can prove to be a useful decision support tool. Furthermore, this GP model can be extended to account for the impacts of higher-quality biomass goals on procurement cost structures once the engineering equations for conversion efficiency in relation to biomass quality have been developed. In general, improved efficiency of CHP and power-only plants would be expected with the use of higher-quality biomass, leading to reduced costs in the value chain for total wood biomass for a given amount of energy, even though the delivery cost may be higher due to the goals requiring higher biomass quality. This trade-off between quality and costs can be modelled. The total biomass demand for each power plant becomes endogenous once the engineering process equations for biomass quality versus conversion efficiency for each type of power plant have been introduced into the model. Development of these equations is a topic for future work.

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REFERENCES