RESIDUAL BIOMASS HARVESTING, CONDITIONING AND TRANSPORT OPERATIONS: PRELIMINARY EVALUATION OF A SYSTEM DYNAMIC MODEL FOR COSTS ESTIMATION AND OPTIMIZATION

Brambilla M.[1], Bisaglia C.[1] and Pari L.[2]

[1] Consiglio per la Ricerca e la Sperimentazione in Agricoltura, Unità di Ricerca per l'Ingegneria Agraria, Laboratorio di Treviglio.

[2] Consiglio per la Ricerca e la Sperimentazione in Agricoltura, Unità di Ricerca per l'Ingegneria Agraria, Monterotondo (Roma).

Corresponding Author: M. Brambilla, CRA-ING, Laboratorio di Treviglio.
Via Milano, 43 – 24047 Treviglio (BG).
massimo.brambilla@entecra.it

ABSTRACT

Residual Biomasses from agriculture and forestry activities are among the most promising renewable energy sources. To face the growing need of such resources for the energy producing industry the delivery of residual biomass fuels must be effectively enhanced compared to the current state. By help of the simulation software "*Vensim DSS*" ® (Ventana Systems Inc.) we developed a set of equations representing one biomass harvesting and supplying chain. The considered system, which has the Time step of one day and covers a time span of three years, is composed by three sub models which are related to: a) energy plant dimensioning; b) supply transport cost estimation; c) harvesting and conditioning operations cost estimation. Model output underwent to univariate and multivariate sensitivity analysis to check its behavior at changing of parameters' values.
Model behavior turns out to be quite robust at varying of the input parameters for all the considered variables: evaluation of behavior pattern measures showed that with reference to €/MWh primary energy equilibrium level is quickly achieved meaning that negative feedback loops become soon dominant in the system.

Keywords: SD Modeling, Biomass Harvesting Optimization.

1. INTRODUCTION

Residual Biomasses (both from agriculture and forestry activities) are among the most promising renewable energy sources whose energetic exploitation may, on one hand, give higher value to residues generally considered as waste materials, while on the other

M. Brambilla, C. Bisaglia, L. Pari "Residual Biomass Harvesting, Conditioning and Transport Operations: preliminary evaluation of a System Dynamic Model For Costs Estimation and Optimization". EFITA-WCCA-CIGR Conference "Sustainable Agriculture through ICT Innovation", Turin, Italy, 24-27 June 2013.

can avoid the occupation of soil for the growth of energy crops (Goldstein, 2006). To face the growing need of such resources for the energy producing industry the delivery of residual biomass fuels must be effectively enhanced compared to the current delivery one. This requires significant changes in the logistics environment of energy plants for sustainable energy production and these changes are furthermore complicated by the sequence-dependent procurement chains for residual biomasses. As consequence of this, optimizing harvesting and supplying operations turns out to be strategic within the framework of the current energy policy. Agricultural systems are by nature complex ecosystems where numerous interacting factors must be taken into account: therefore there is the need of a quantitative whole system approach to help optimize such complex interacting factors (Lai et al., 2011). To this purpose, we developed the conceptual model of one decision support system (DSS) with the final aim to optimize biomass supply costs for a given energy plant run with renewable fuels. Its undoubted that model parameters, in system dynamics models, are subject to uncertainty which may yield unreliable simulation results especially in case these models have nonlinear and complex structures. For this reason the present paper focuses on the sensitivity analysis of a biomass chain production and delivery model.

2. MATERIAL AND METHODS

By help of the simulation software "Vensim DSS" ® (Ventana Systems Inc.) we developed a set of equations representing one biomass harvesting and supplying chain with a chosen time resolution of one day. In the simulation, the time-integrated behavior of the system, is reproduced. The general approach and the compartments required were mapped out using the logic rules implicit in the software (Eberlein et al., 1992).
The hypothesized scenario is that of a biomass fed power plant where wood fuel is supplied through the set-up of a residual biomass conditioning and supply chain where trucks of different capacity can be used. The model was set up to cover a time span of 1096 days (three years).
Input variables are grouped according to three main subgroups which are enlightened in Fig.1 by different colored dotted rectangles:

a) Variables for power plant dimensioning (red)
b) Variables identifying biomass transport costs estimation (green)
c) Variables identifying biomass harvesting and conditioning (blue)

To evaluate model robustness and assess its susceptibility to parameters' uncertainty, model output was formerly tested performing the statistical screening proposed by Ford et al. (2005) and Taylor et al.(2007; 2010). After this, the model was subjected to behavior pattern sensitivity (meaning changes of behavior mode in response to changing model parameters) whose information not only indicates, the important parameters of the model, but also provides useful information for leverage points of the system.

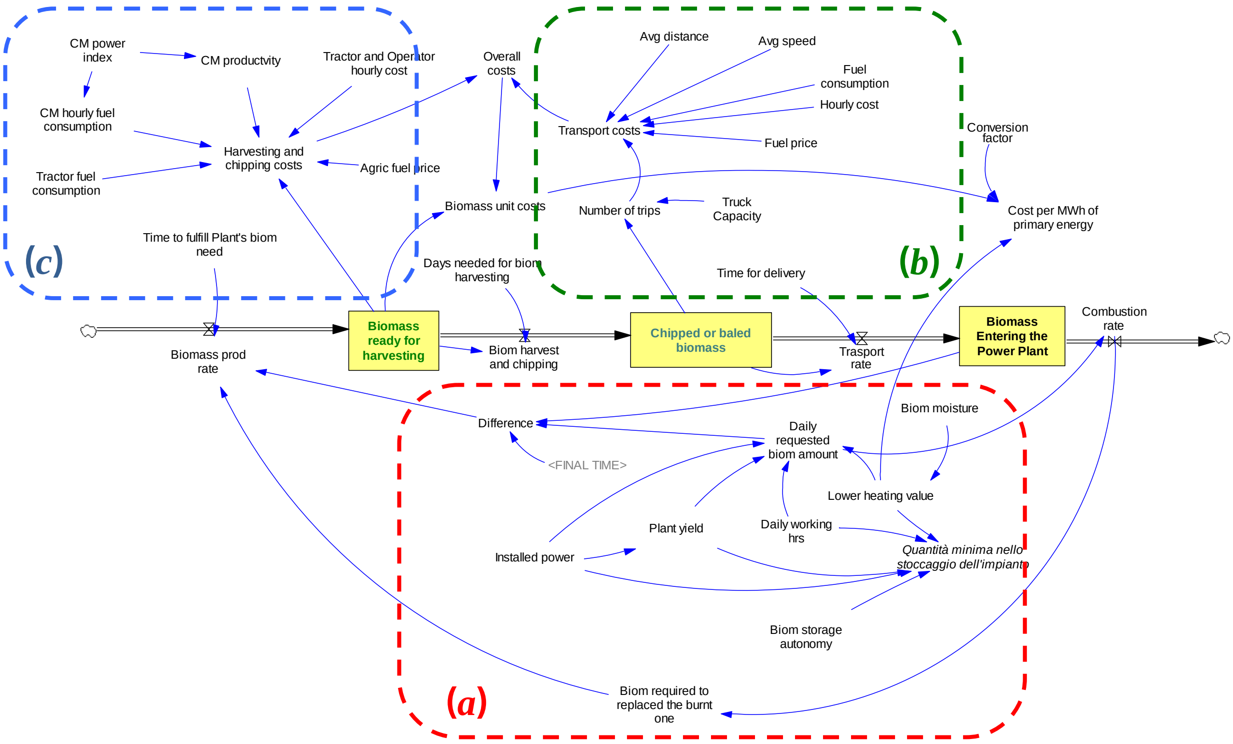

Figure 1. Sketch of the proposed model containing the logical links between the considered variables.

Parameters and their distribution information were entered to Vensim's Sensitivity Simulation module as described in the study by Ford et al. (2005) assuming that each parameter value had uniform distribution within these ranges. These values are reported in table 1.

Table 1. Input parameter distributions

Model Subgroup	Parameter	Range	
		Min	Max
a	Daily working hours	22	24
	Biomass moisture (%)	10	30
b	Average distance (km)	5	70
	Fuel consumption (L/h)	2.5	3.5
	Fuel price (€/L)	1.666	1.977
	Truck capacity (Mg)	18	22
	Time for delivery (Day)	1	15
	Hourly cost (€/h)	65	70
c	Tractor fuel consumption (L/h)	6	9
	Agric. Fuel price (€/L)	0.9	1.1
	Time to fulfil p.p. biom. need (Day)	60	180
	Tractor + operators hourly cost (€/h)	45	55

According to Ford et al. (2005), Hekimoğlu (2010) and Hekimoğlu et al. (2010), the software was set to sample 300 simulation runs by using Latin hypercube sampling (LHS). Sensitivity graphs showing the 50%, 75%, 95% and 100% confidence bounds are reported in figure 3.

Statistical screening was subsequently performed calculating the simple correlation coefficients between the changing parameters and the sensitivity output and plotting the correlation coefficient time series in one graph and, according to model output, looking at particular time periods, to highlight which variable are the most correlated (Fig. 3 and Fig. 4.).

On the other hand, when behavior measure estimation procedure is concerned, we took into account points (in time) where the effect of each feedback loop turns out to be significant: peak points and inflection points. These have been pointed out from model runs by mathematical comparison as the output behavior is a function of time and other model constant. The points we need to determine are the maximum(s), quite easily detectable, and inflection times. These, under the mathematical point of view, are time points at which the second derivative of the pattern becomes negative when we take the derivative of the pattern with respect to time. Moreover, in these points the second derivative of a function shifts to negative, the first derivative is at maximum. Therefore, we calculate differences between successive time points and take the maximum of these differences as inflection time (Scotto Lavina, 1994). When these points are pointed out, for each of them, the standardized regression coefficients where calculated as they give the importance of independent variables for the dependent one in a regression equation: according to Saltelli et al. (2000), the simulation model is more sensitive to the parameters that have larger-magnitude regression coefficients in the regression equation.

3. RESULTS

Figure 2 reports the sensitivity output of the model for four of the variables (the three levels plus the auxiliary one related to the costs per MWh of primary energy). It can be noticed that model behavior is quite robust because of the uniformity of the obtained patterns (Coyle, 1996).

Statistical screening results shown in Figure 3 paint a dynamic picture of how input parameters influence the behavior of the variable “Cost per MWh of primary energy” which has been chosen as performance variable for such analysis. Comparing the correlation coefficients turns out that the most influencing variables (whose “r” is above 0.2)are “Tractor + Op. Hourly cost”, “Time for Delivery”, “Average Distance” and “Agricultural Fuel Price”. In particular, it turns out that with particular reference to the first two months of simulation (when the biomass chain starts) the costs related to harvesting and chipping operations have a big “positive weight” on variable output while from the third onwards, the time required for delivering biomass to the power plant reaches almost the same importance. Things are slightly different when costs are related to each Mg of produced biomass (Fig. 4): here, according to the method proposed by Ford et al. (2005), the most influencing variables turn out to be “Time for delivery" and "Average distance" whose correlation coefficient is just slightly above 0.2 throughout the simulation.

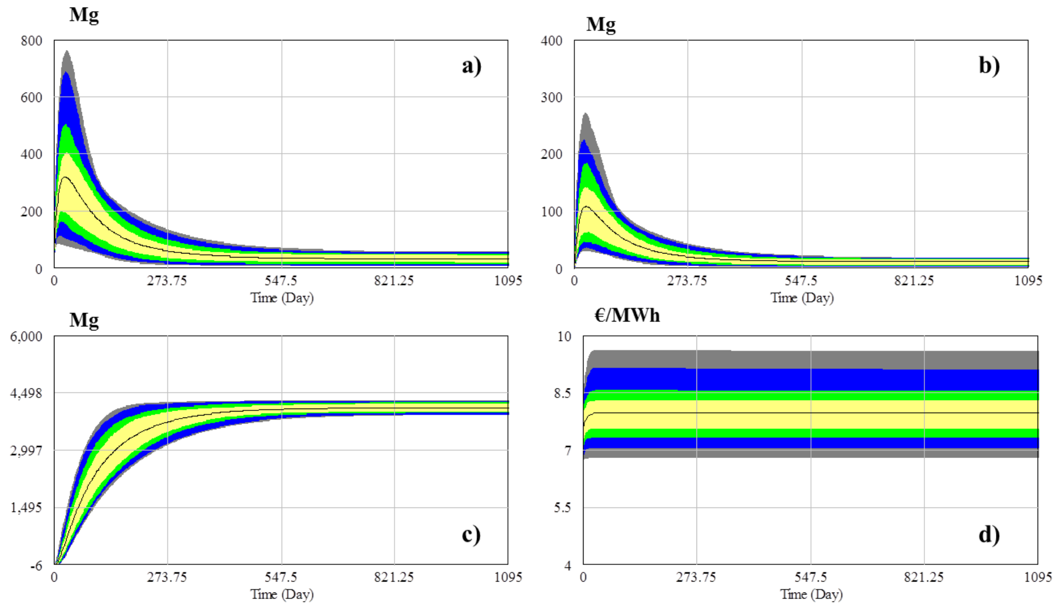

Figure 2. Sensitivity output of "*Biomass ready for harvesting*" (a), "*Chipped or baled biomass*" (b), "*Biomass entering the Power Plant"* (c), "*Cost per MWh of primary energy"* (d) with confidence bounds (50%, yellow, 75%, green, 95%, blue, 100% grey).

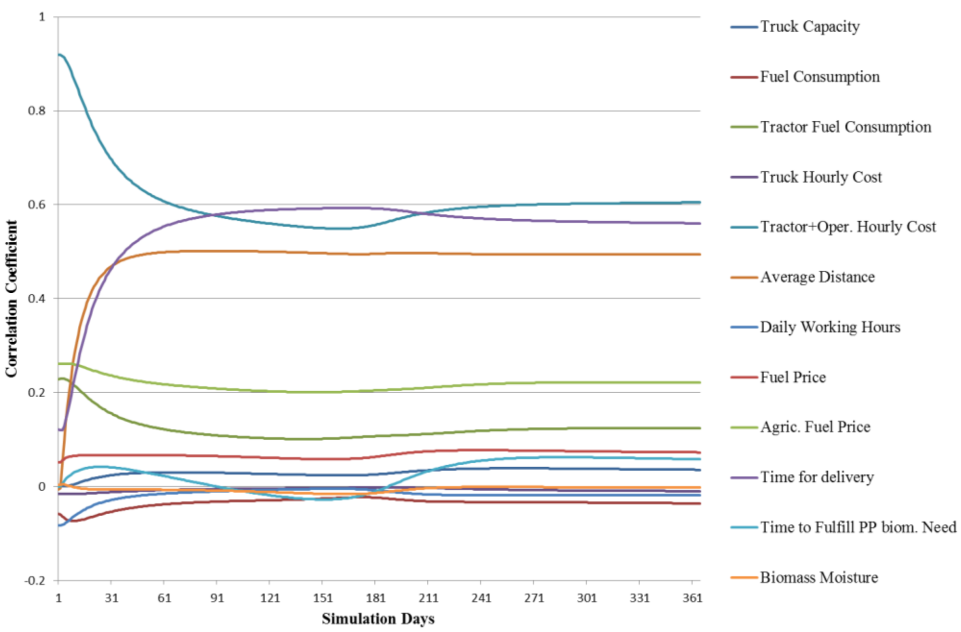

Figure 3. statistical screening of the "*Cost per MWh of primary energy*" variable (simulation days limited to the first year of simulation).

P0089
M. Brambilla, C. Bisaglia, L. Pari "Residual Biomass Harvesting, Conditioning and Transport Operations: preliminary evaluation of a System Dynamic Model For Costs Estimation and Optimization". EFITA-WCCA-CIGR Conference "Sustainable Agriculture through ICT Innovation", Turin, Italy, 24-27 June 2013.

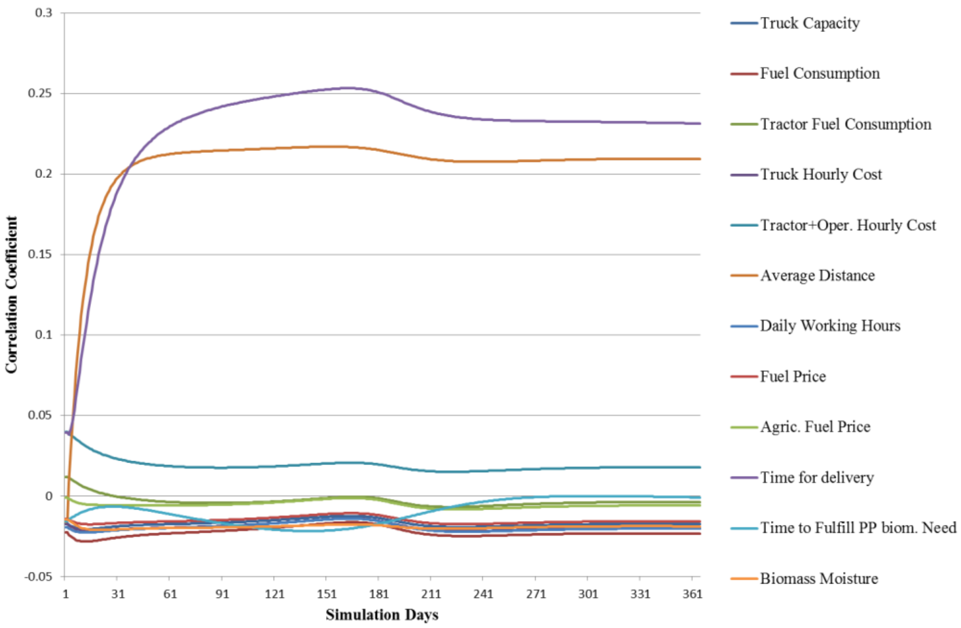

Figure 4. statistical screening of the "*Cost per Mg of harvested biomass*" variable (simulation days limited to the first year of simulation).

Behavior pattern analysis carried out on the variables displayed in Fig. 2 pointed out the presence of peak points, inflection points and equilibrium levels whose meaning needs to be related to model structure: *peak point* and the related *time of peak* are measures describing the relative strengths of the feedback loops shown in Fig. 1. The *inflection point* of a s-shaped growth is the point up to which the system follows exponential growth meaning that positive feedback loops are dominant in the system (therefore, inflection point level of the behavior is related to the initial strength of the positive feedback loop) while *inflection time* indicates the time when negative feedback loops become dominant in the system and both measures are very similar to each other. Lastly, *time to reach equilibrium*, which provides idea about the strength of the negative feedback loop, is another measure of s-shaped growth.
With reference to the "*Cost per MWh of primary energy"* variable, behaviour analysis showed the presence of two inflection times: one at day 72 (Table 1) and one at day 167 (results not displayed).
With reference to Table 1, given that regression results not only indicate the most influential parameters of the model but also the signs of coefficients indicate the "direction" of the correlation between the parameter and inflection point, turns out how variables connected to biomass harvest and conditioning costs are effective in increasing the value of the variable. On the other hand, variables connected to biomass transport and delivery, having negative coefficient, are those which at the beginning of the simulation do not affect the considered variable at high extent. Things turn out to be quite different at the 167th day of the simulation when, according to regression analysis, the relative weight of variables connected to biomass delivery significantly increases

while those of the variables related to biomass harvesting remain quite constant meaning that at this point this is the feedback loop which assumes dominant position in such system.

Table 1. Linear regression results for the "*Cost per MWh of primary energy*" variable

Parameter	Day 2			Day 167		
	Coeff.	S.E. Coeff.	P	Coeff.	S.E. Coeff.	P
Daily working hours	-0.013	0.0011	0.000	-0.0048	0.018	0.793
Biomass moisture	-0.00004	0.0001	0.771	-0.0023	0.0022	0.308
Average distance	0.00004	0.00004	0.339	0.0176	0.00068	0.000
Fuel consumption	-0.0055	0.0029	0.063	-0.048	0.046	0.293
Fuel price	-0.035	0.0089	0.000	-0.212	0.139	0.129
Truck capacity	-0.0026	0.0007	0.000	-0.027	0.011	0.014
Time for delivery	0.00015	0.0002	0.476	0.088	0.0032	0.000
Hourly cost	-0.0049	0.0004	0.000	0.001	0.007	0.880
Tractor fuel consumption	0.116	0.00094	0.000	0.123	0.015	0.000
Agric. fuel price	1.62	0.014	0.000	1.62	0.226	0.000
Time to fulfil p.p. biom. need	-0.000014	0.00002	0.561	-0.0018	0.0003	0.000
Tractor + operators hourly cost	0.116	0.00028	0.000	0.113	0.004	0.000

4. CONCLUSION

One biomass supply chain model was set up with the aim of estimating costs connected to residual biomass harvesting, conditioning and delivery. The model behavior was checked using "*Cost per MWh of primary energy*" as target variable. Statistical screening and model behaviour analyses show the importance of biomass harvest and conditioning at as cost increasing factors in the initial phases of the simulation. Further work still need to be performed to validate it with independent sets of data.

5. ACKNOWLEDGEMENTS

The authors acknowledge the role of the project "*Energie da biomasse agricole e forestali: miglioramento ed integrazione delle filiere di biocarburanti e della filiera di produzione di energia elettrica e termica*" (DM 4723 del 18/10/06) for funding the contract N. 831/2a-c.p.

6. REFERENCES

Coyle, R. G. 1996. System Dynamics Modelling, a Practical Approach. Chapman & Hall, Boca Raton, Fl, USA. ISBN: 978-0-412-61710-2.

Eberlein, B., Peterson, D. W. 1992. Undertaking models with Vensim ®. European Journal of Operational research, 59 (1), 216-219.

Ford, A., Flynn, H. 2005. Statistical Screening of System Dynamic Models. System Dynamics Review 21 (4): 273–303.

Goldstein, N. 2006. Woody biomass as a renewable energy source. Biocycle, 47(11): 29-31.

Hekimoğlu, M. 2010. A Methodology for statistical sensitivity analysis of System Dynamic Models. Thesis Submitted to the Institute for Graduate Studies in Science and Engineering in partial fulfillment of the requirements for the degree of Master of Science. (http://www.ie.boun.edu.tr - Accessed March 2013).

Hekimoğlu, M., Barlas, Y. 2010. Sensitivity Analysis of System Dynamic Models by Behavior Pattern Measures. Proc. of the 28th International Conference of the System Dynamics Society. July 25th – 29th, Seoul (Korea).

Lai, R. A., Liwang, M. (Eds.). 2011. Methods of Introducing System Models into Agricultural Research. American Society of Agronomy, Crop Science Society of America, Soil Science Society of America ISBN: 978-0-89118-180-4.

Minitab® 16 Statistical Software 2010. [Computer software]. State College, PA: Minitab, Inc. (www.minitab.com).

Saltelli, A., Chan, K., Scott, E. M. (eds). 2000. Sensitivity Analysis. John Wiley & Sons. ISBN: 978-0-470-74382-9.

Scotto Lavina, G. 1994. Esercitazioni di meccanica applicata alle machine. Edizioni Scientifiche Siderea, Roma, Italia.

Taylor T., D. Ford and A. Ford, 2007. Model analysis using statistical screening: extensions and example applications, Proceedings of the 25th International Conference of the System Dynamics Society, 29 July - 2 August 2007, Boston.

Taylor T., D. Ford and A. Ford, 2010, Improving model understanding using statistical screening, System Dynamics Review, Vol.26, No.2, pp.73-87.
