XVIII ICIEOM 2012
International Conference on Industrial Engineering and Operations Management
Guimarães - Portugal July 9 - 11, 2012

Simulation Optimization Model for Analysis of Inventory of Carbon Monoxide Emissions

Leonardo das Dores Cardoso*, João José de Assis Rangel+, Eglon Rhuan Salazar Guimarães+, Dalessandro Soares Vianna+

* IFF - Instituto Federal Fluminense, Brasil.
+ UCAM - Universidade Candido Mendes, Brasil.

Email: leocardoso@iff.edu.br, joao@ucam-campos.br, eglon.rhuan@gmail.com , dalessandro@ucam-campos.br

Abstract

This paper presents an analysis of inventory of carbon monoxide emissions using a discrete event simulation model integrated with a combinatorial optimization model. The analysis addresses the rate of emission of gases in a system of sugarcane transport, typically used in the mills. Environmental issues, such as controlling the emission of greenhouse gases, are at the heart of business decisions. This statement applies both to Brazil and others countries. Gradually, whether through sanctions, or by government incentives and entrepreneurial vision of sustainable companies, this has been a relevant factor in resource allocation. The simulation optimization model was adequate to analyze the greenhouse gas inventory and the results were consistent with the levels of emissions of gases, set in standards here and abroad.

Keywords: Discrete Event Simulation; Simulation Optimization; Genetic Algorithm; Sustainability, Emissions Inventories.

1 Introduction

In recent studies, Zhou and Kuhl (2009, 2010 and 2011) show the structure of a simulation toolkit to analyze the greenhouse gas emission. This kit allows the use of discrete event simulation to analyze factors related to the greenhouse gas emission along with traditional measures of productivity and sustainability. Similarly, Widok and Wohlgemuth (2011) attempt to highlight shortcomings in the concept of sustainability and ways to make the concept more workable by presenting the development of an Environmental Management Information System (EMIS) as a combination of discrete event simulation and ecological material flow analysis for production. Page and Wohlgemuth (2006) combine discrete event simulation and analysis of material flow in an approach based on components for protection of the industrial environment.

On the other hand, simulation combined with optimization has been of great interest in research for over a decade. Fu (2002) highlights the applicability of the integrated optimization to simulation to evaluate various types of problems. In most recent work, Huang et al. (2010) use discrete event simulation and optimization to the management of water resources in Tarim River basin, China. These works are part of the applicability of these approaches for sustainable analysis of problems. The integration of both approaches provides a more comprehensive evaluation than each one separated, thus, getting inherent advantages to both of them. Among the main advantages, there is the possibility of adding to optimization the random factor of the input data to be analyzed. Thus, the values can be represented by statistical distributions, making input data closest to the real data, something rarely used in pure optimization. However, using the simulation, even though enables the analysis of various scenarios, requires the individual execution of each of these. This process generates good results, but may be very tiring, consume a lot of time and, in most cases, may not guarantee the best configurations of results (PINHO, 2008).

In this context, this paper presents an analysis of emission inventory of carbon monoxide (CO) using a model of discrete event simulation integrated into a model of combinatorial optimization. The analysis addresses the rate of gases emission in a hypothetical system of sugarcane transport, typically used in sugarcane mills. Environmental issues, such as the control of greenhouse gas emission, are at the heart of business decisions. This statement applies to Brazil as well as other countries. With the imminent need to reduce the rates of greenhouse gas emission, there is a necessity for solutions that do not compromise productivity and high-cost. Gradually, whether through punishment, government incentives or the entrepreneurial and sustainable vision of the enterprises, this has been a relevant factor in resource allocation. Like other companies, aiming to meet the interest groups increasingly demanding, the sugarcane sector seeks to management models that meet mutual interests related to sustainability, quality, environmental responsibility and consumer market (OLIVEIRA, 2007; PEREIRA et al, 2010).

2 Problem Description

The hypothetical logistics system used took into account the sugarcane transport typically used in sugarcane mills and described in works as in Rangel et al. (2010); Iannoni & Morabito (2002). Figure 1 shows, schematically, the receiving system of sugarcane used. This system considered 5 (five) harvest front (HF), each supplying sugarcane for a mill by means of 5 (five) trucks allocated on each HF.

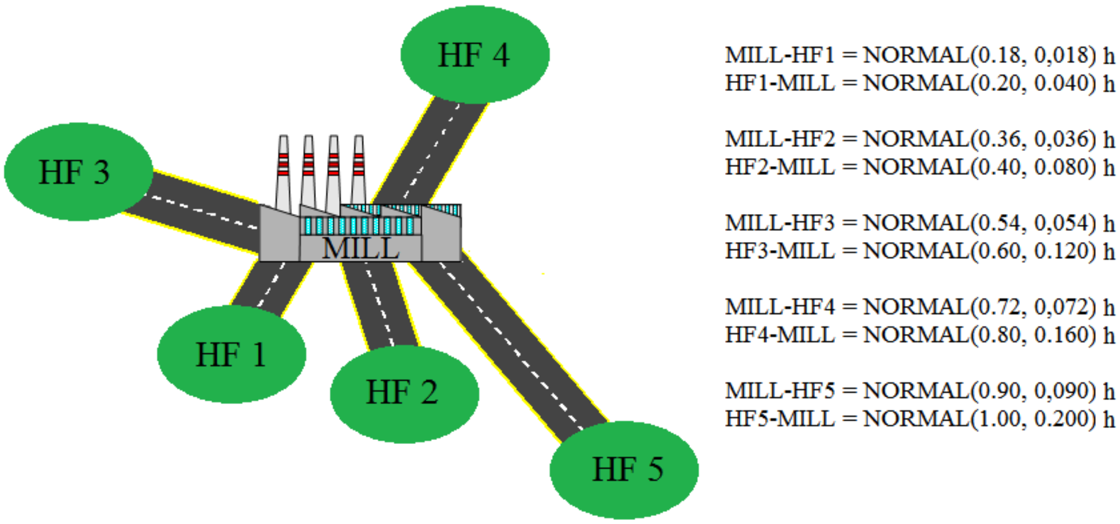

Figure 1: Logistics system of sugarcane transport and transport time from the harvest front to the mill

To regulate the emissions of pollutants in Brazil, the Environment National Council (CONAMA – in Portuguese) created the Control Program of Air Pollution by Motor Vehicles (PROCONVE – in Portuguese). This program follows the Standards Euro of Air Pollution and has as the main objective, according to Resolution 315/02 of CONAMA in its Art 1º, "to reduce the emission levels of pollutants in motor vehicles and promote national technological development, both in engineering of design and manufacturing, as in methods and equipment to control the emission of pollutants ".

This way, the data used for the preparation of the model followed the same Resolution 315/02 of CONAMA. This one establishes new stages to PROCONVE, which follows the standards Euro on rules of emissions of pollutants from automobiles sold in European Union countries. These standards have been adopted by the European Union since 1991. Table 1 illustrates the situation of Brazil since the beginning of the implementation of such standards in 1989. Currently, it follows the P6 with much lower emission levels compared to those allowed from the start. It may be noted that while Brazil has adopted the P6, which follows the standard Euro 4, the European Union has already adopted the standard Euro 5. Although the level of CO is the same in Euro 4 and 5, it is noteworthy that the levels of emissions of other pollutants have been reduced from one standard to the other.

Table 1: PROCONVE phases and their respective rates

PROCONVE	EURO	CO (g/kW.h)	TERM	STANDARD (CONAMA)
Phase I (P1)	Without Specification	14.00	1989 to 1993	Res. 18/86
Phase II (P2)	Euro 0	11.20	1994 to 1995	Res. 08/93
Phase III (P3)	Euro 1	4.90	1995 to 1999	Res. 08/93
Phase IV (P4)	Euro 2	4.00	2000 to 2005	Res. 08/93
Phase V (P5)	Euro 3	2.10	2006 to 2008	Res. 315/02
Phase VI (P6)	Euro 4	1.50	2009 to 2012	Res. 315/02
Phase VII (P7)	Euro 5	1.50	From 2012	Res. 403/08

In this study, we analyzed only the factor CO, but the model could be used to analyze emissions of hydrocarbons (HC), nitrogen oxides (NOx) or particulate material (PM), among other elements normally used for calculating inventory emissions.

Furthermore, analysis with mixed fleets (vehicles of different years of manufacture, which cater to different emission standards) can be performed, enabling decision-making considering the environmental factor.

The randomness is considered by the model in the time factor, taking into account that the traffic of the fleet will not have a constant time. It was considered that 90% of the total power available from the truck are used in the transportation of sugarcane from the harvest front to the mill. In return from the mill to the HF, with the empty truck, it was considered that only 40% of the available power of the truck are used. Thus, the emission of pollutants in return is lower due to the fewer load transported. In the model, the power may vary from 90 to 130 kilowatts, depending on the type of truck. Similarly, the capacity may vary from 10 to 18 tons.

Among the 25 trucks in the fleet, each group of 5 represents one of the first five phases of PROCONVE. This way, 5 trucks meet Phase I (P1), generate 90 kilowatts of power and carry 10 tons. Other 5 meet Phase II, generate 100 kilowatts of power and carry 12 tons and so on. The amount of emissions generated by burning fuel is a function of several parameters, including the fuel type, the engine power of the truck and the time the engine is running (MANICOM et al. 1993). These results provide a list of emission factors in the unit of grams per kilowatt hour (g / kW · hr) for various types of fuels, including diesel. Thus, we have the relationships shown in Equation 1:

$$\mathbf{E_x(t) = C_{co} * Pot * t} \tag{1}$$

Where the produced emissions (*E*) of the vehicle (*x*) along the time interval (*t*) are equal to the emission coefficient (C_{co} of vehicle *x*) times the power of the truck in kW (*Pot*), still multiplied by the time period (*t*) (ZHOU; KUHL, 2010).

3 Simulation Model

The methodology by Freitas Filho (2008) was followed, to prepare this simulation project, with the next steps: formulation and analysis of the problem; project planning; gathering of macro-information and data; modeling of the input data; construction of the conceptual model; verification and validation; experimentation; interpretation and statistical analysis of the results; comparison and identification of the best solutions; and documentation and presentation of results.

From the IDEF-SIM technique (Montevechi et al, 2010), it was possible to construct the conceptual model of the process with a visual aspect of easy understanding and logic similar to that used in programming of the computational model. The conceptual model to carry out computer simulations was translated into software Arena ® 12 of Rockwell Automation to carry out computer simulations (Kelton et al. 2007). Figure 2 shows the conceptual model of the system.

It was used, in addition, the methodology proposed by Sargent (2011) for the verification and validation of the model. It is worth mentioning that the computational model was constructed after the conceptual model is ready, fully verified and validated (SCHRIBER AND BRUNNER, 2011; CHWIF and Medina, 2010).

We used distribution functions of the Normal type to describe the dynamics of the processes. The Normal function may be used whenever the randomness is caused by various independent sources, acting in an additive way around a middle point (FREITAS Son, 2008).

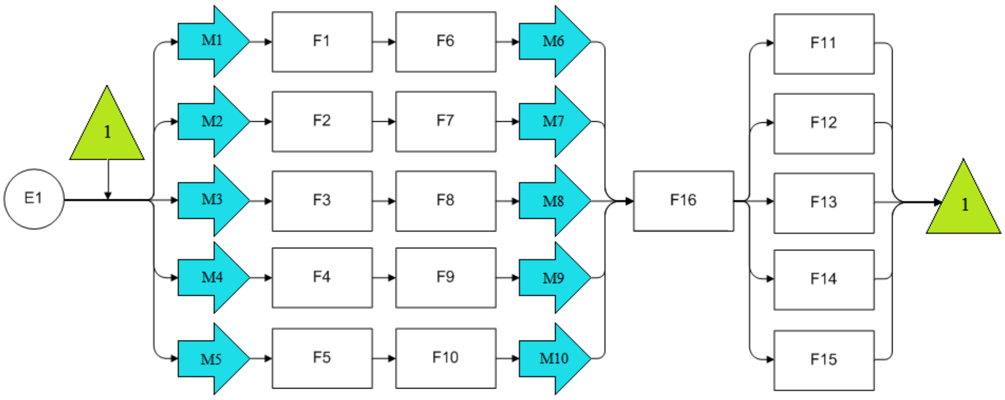

Figure 2: Conceptual Model of the IDEF-SIM – system

The simulated system begins with the acquisition, by the simulation model, of the time needed for the departure of each of the trucks (E1) to the corresponding HF. This path has variable time, since they are at different distances from the mill and may suffer changes generated by factors as traffic. From these, the optimization is performed (as described in item 4) in order to allocate each truck to a HF.

Then, the trucks follow to their respective HC (F1, F2, F3, F4 and F5). In this way, the pollutants are emitted, with emissions recorded in CO emissions inventory through the functions F6, F7, F8, F9 and F10. Arriving at HC, the trucks are loaded (F11). The loading and unloading times are not counted in the emissions inventory, since they are performed with the engine off.

Once loaded, the truck returns to the mill, represented by functions F12, F13, F14, F15 and F16, where it waits until the unloading of sugarcane is done (F22). The functions F17, F18, F19, F20 and F21 register the emissions generated by the return of it to the mill. After this process is conducted, a new loading cycle is started.

It is noteworthy that the round of simulation took into account one day of 8, 12 or 24 hours. In this sense, the system is characterized as a terminal system, because it presents initial flat condition and an event which determines a natural end to the simulation process(Law, 2007).

4 Optimization Model

Presented by Holland (1975), known as canonical, and increased in later works such as Goldberg (1989), Davis (1990), Michalewicz (1996), Bäck et al. (2000a), genetic algorithms (GA) belong to a class of probabilistic algorithms based on biological evolution (DIAGALAKIS et al, 2000). The GA's simulate biological processes of genetic recombination, mutation and selection, providing solutions for a given problem.

This metaheuristic has been shown efficient for solving various problems. As examples, there may be mentioned the study by Costa et al (2011), which analyzes how to obtain consistency in the analytic hierarchy process. Coelho et al (2006) apply genetic algorithms in the solution of problems of cell clusters. Pezzella et al (2008) uses a genetic algorithm for the Flexible Job-shop Scheduling Problem. In the same year, Yang et al (2008) uses genetic algorithm for stand-alone hybrid solar-wind system with LPSP technology.

The proposed GA differs from canonical, mainly, due to specific restrictions of the problem to be analyzed:

1. An initial population not only random but greedy;

2. disturbances (inversion of bits) are carried out in random positions of the greedy individual for creation of 50% of the population;

3. the mutation is not performed by changing the genes for random values, but through inversion in these positions;

4. as an HF cannot own more than 5 trucks, individuals with more than 5 trucks in the same HF are eliminated.

The individual consists of 25 genes, in which each gene can vary in value between 1 and 5, due to the nature of the problem. These values represent the possible HF that each truck can be allocated. The truck fleet is represented in the individual so that the first 5 positions of the vector represent a type of truck; the next 5 represent another type of trucks and so on. This approach was developed because it allows representing the individual in a simple vector of 25 positions, facilitating the calculation of the fitness of each one, since the models of trucks obey a sequence.

The present work aims to minimize the amount of carbon monoxide emitted by the heterogeneous fleet of trucks without causing serious damage to the quantity shipped. Thus, the GA submitted allocates trucks to minimize the amount emitted by the fleet to carry a ton of cane from HF to the mill, as shown in Equation 2:

$$\textbf{Min } Z = \sum E_{CO} / \sum T_{Cana} \qquad (2)$$

Where it is expected minimize the function Z. This function is formed by the emitted amount of CO, which is equal to the sum of CO emitted by each truck in grams (ECO), divided by the transported quantity of sugarcane, which is equal to the sum of the amount carried by each truck in tons (T_{Cane}).

The structure of the proposed algorithm is represented in the flowchart of Figure 3. The differences from the proposed GA to the canonical are described in Sections 3.3 and 3.4 and are due to the constraints of the problem addressed.

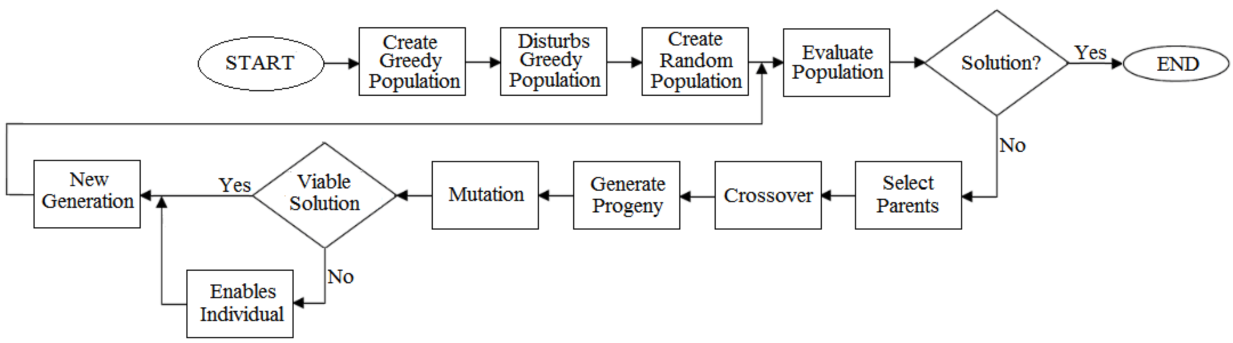

Figure 3: Flowchart of the proposed GA, developed from modifications of the method proposed by Holland, 1975.

4.1 Initial Population

At this stage, we define the initial population, which will be stored in a set of elements, usually divided into a vector, matrices or list of data. These are available from the generation of binary strings obtained by individuals composed by data set (chromosomes).

In GAs complex that use constructive heuristics the generation of the initial population is such as the computer model that is presented and uses the combination of the Random and Greedy techniques. The proposed GA uses three constructive methods from which the necessary solutions were generated for the composition of the population. The first constructive allows generating, in a greedy way, a chromosome on the criterion of the minimum CO emission; a second, depending on the maximum amount of tons of sugar possible to be transported in a period of one hour, in all the harvest fronts. In the third, disorders are made in these two chromosomes.

According to the greedy criterion, a greedy chromosome is selected and 3 genes of the same are altered to create the other chromosomes. Figure 4 shows the exchange of material between the gene of the 3-position of the vector, value 3, with the gene of number 14, of value 5. This means that the truck 3, which was allocated in HF 3, was relocated to the HF of cut 14. Truck 5 that was in HF 14 was assigned to HF 3. The same occurs with the genes of numbers 8 and 12 and genes 16 and 18.

These bits to be changed are randomly selected. Thus, half of the initial population is created from the 2 greedy chromosomes and disorders made on them. In the third and final construction method, new chromosomes are generated in a totally random way, completing the initial population.

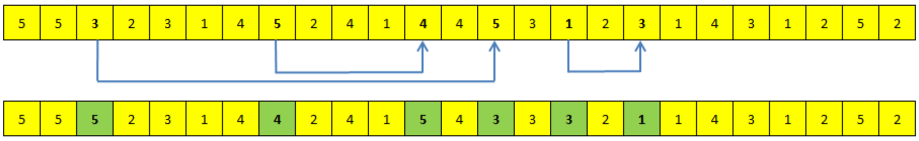

Figure 4: Disorder performed in greedy solutions.

4.2 Operators

4.2.1 Crossover

At this stage, the crossover of individuals (crossover) is performed, thus, getting children who have parental characteristics selectively. The goal is to seek best features for continuation of the interactive process (in this case, the worst children will be dropped).

The process is carried out from a cut point in the chromosomes, dividing them into parts for the generation of obtained children. The intersection with a cut point is the simplest way of implementation of the crossover operator, where two individuals of the population, after selection, are subjected to the crossover process. This crossover process takes place as follows: the cut point is randomly generated , and this is less than or equal to the length of the chromosome. Then, the characters preceding the cut point are preserved, and the subsequent characters are exchanged between the participant pair (parents) in the process.

Figure 5 illustrates the operation of crossover of a cut point. In this individual, the cut was made between the seventh and eighth gene (this cut position is randomly selected in this work). In blue, we have genes that will be maintained and, in green and yellow, genes to be exchanged, thus, generating new descendants.

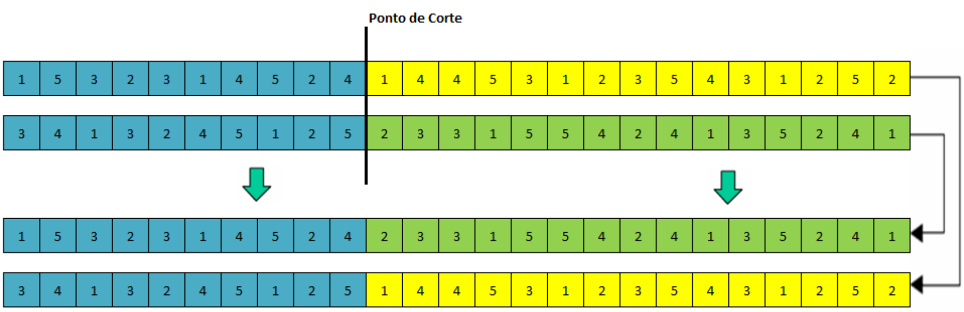

Figure 5: Crossing with a cut point.

4.2.2 Mutation

At this stage, the data structure is maintained. Yet, changes in genes are generated in order to increase the diversity of chromosomes, circumventing the problem of local optima.

In the process of mutation, all the genes of the chromosome are traversed and, according to the probability of mutation rate (typically from 0.1% to 5%), the inversion takes place. Figure 6 illustrates the situation in which, in traversing the chromosome, we selected the 3rd and 5th chromosome gene to mutation takes place. The value of the 3rd gene, 3, was inverted to the value of the 5th gene, 5, generating a change in the individual.

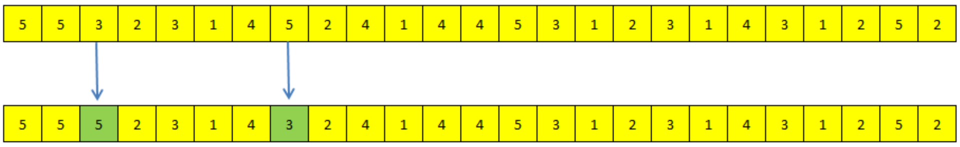

Figure 6: Mutation by exchanging 2 random genes.

Cartwright (1995) states that the effect of the mutation operation is twofold, as it can be seen as followed: Firstly, it provides a mechanism where values not present in the chromosomes of the initial population can be generated. Secondly, it prevents the stagnation of the population. The mutation improves the diversity of the chromosomes in the population, however, destroys information contained in the chromosome. Therefore, a small rate of mutation (usually 0.1% to 5%) must be used, but sufficient to ensure diversity.

In the proposed algorithm, the mutation is not done randomly. The mutation is made from the random exchange of material between 2 genes, ensuring a diversity of solutions due to constraints of the problem discussed earlier. It was empirically defined the mutation rate of 1% after testing the performance of the optimizer.

4.2.3 Selection

At this stage, we try to select the best individuals for the crossing, thus, aiming at the evolution for future generations. There are several methods for making such a selection, such as Random Selection, Roulette, Tournament; Deterministic Selection, Stochastic Selection by Remainder With and Without Replacement; Selection by ranking, and so on.

The selection method used was Roulette, proposed by Holland (1975). Its operation is based on the probability of each individual to be selected. This probability is found by obtaining the ratio of the objective function of each individual of the population by the sum of objective functions of all individuals.

4.2.4 Make Feasible Solution

As the process of crossing between individuals (parents) does not guarantee that the new individuals (children) meet the assumptions of the problem (just 5 trucks associated with the same HF), it was necessary to develop a procedure to detect the harvest fronts with a different quantity of trucks. Randomly, a gene, which results in a number of trucks on a harvest front beyond the 5 set, is removed and replaced until all the harvest fronts have 5 trucks.

5 Experiments

The experiments were performed in a computer with a 2.27 GHz processor and 3GB of principal memory.

The instance used was proposed by Cardoso et al (2011). This was, originally, used to analyze the emissions inventory using a standard discrete event simulation. Some changes were made for further analysis using the optimization of the simulation.

It would be necessary the creation of scenarios with the possible combinations of allocations of the trucks to test the performance of the model developed without the integration of the optimizer. The number of combinations would be 2^k scenarios (Mattos et al, 2008; MONTGOMERY, 2009; Montevechi et al, 2010), resulting in 32 scenarios. It is possible to perform the analysis without creating them due to the integration of generic algorithm. Table 2 presents data obtained from the pure simulation model. Among the 32 possible scenarios, this is the one with the worst outcome. This could represent a real situation, and will be used for analysis in sets with data obtained with the integration of the optimizer. Table 3 presents the data obtained by the model integrated with the optimizer.

Table 2: Data obtained from the simulation model to 8, 12 and 24 hours of transport.

Scenario	Transport time (h)	Individual	Emission (g)	Transport (Ton)	Emission/ Transport (g/Ton)
1	8	11111222223333344444455555	101466	5314	19,09
2	12	11111222223333344444455555	154347	8067	19,13
3	24	11111222223333344444455555	312609	16231	19,26
				Média	19,16

Table 3: Data obtained from the integrated simulation model to the optimizer for 8, 12 and 24 hours of transport

Scenario	Transport time (h)	Individual	Emission (g)	Transport (Ton)	Emission/ Transport (g/Ton)
1	8	55555444443333331222211112	125401	7054	17,78
2	12	55555444443333332122212111	189615	10949	17,32
3	24	55555444443333332221211112	389815	23077	16,89
				Média	17,33

It is possible to note that the results of the simulation model have absolute values of low emissions, but with a significant reduction in the quantity transported. When comparing the values of the emitted amount to transport a ton of sugarcane, of the results obtained by this (Table 1) with the results obtained by the optimizer (Table 2), it is observed that the latter has a lower rate of emission. This feature shows the results obtained by the optimizer as the best long-term, since all cane produced will be transported to the mill.

Considering that the total quantity of cane to be transported to the mill is 4279860 ton - value related to the harvest of 2005 of the municipality of Campos dos Goytacazes according to IBGE (2005) at a rate of emission of 19.16 g / ton (average rate of emission with the allocation made by the simulator), it would be emitted 82,002,118 g of CO. While at a rate of 17.33 g / ton (average rate of emission with the allocation made by the optimizer), it would be emitted 74.169.974g. This value would result in the emission of up 7.823.144g of carbon monoxide less.

It is still not excluded that it would take approximately 263.7 days to transport all production with the allocation made by the simulator, considering a journey of 24 hours worked. While the one made with the aid of the optimizer would take approximately 185.4 days, resulting 78.3 days less. A reduction of 9.54% in the amount of emitted CO and 29.69% in the amount carried on days.

6 Concluding Remarks

The simulation model with optimization developed was adequate to analyze the inventory of CO emissions, and the results were consistent with the levels of gas emissions expected in Brazilian and international standards.

The optimization model tested various possible combinations in the simulation model in search of an optimal solution to the problem. The integration of simulation with optimization enabled a more rapid and less exhaustive analysis by eliminating less relevant scenarios.

The results showed that the best way to reduce the amount emitted could be the replacement of older trucks (carry less load and emit more pollutants) for newer trucks. However, using the GA, it was possible to reduce the emission of pollutants by up to 9.54% without exonerating these costs, and enabled an increase in the quantity transported by up to 29.69%.

Finally, it was stated that the integration of the two approaches proved to be efficient for sustainable allocation of a fleet of heterogeneous trucks in the evaluated system.

Acknowledgments

The authors would like to thank the National Council for Scientific and Technological Development - CNPq, and the Foundation for Research Support of Rio de Janeiro - FAPERJ for financial support for this research.

References

BÄCK, T.; FOGEL, D. B.; MICHALEWICZ, Z. (2000), Evolutionary Computation1: Basic Algorithms and Operators, Institute of Physics Publishing, 2000.

BRASIL, DISTRITO FEDERAL. (20 de novembro de 2002). Resolução n. 315, de 29 de Outubro de 2002. Dispõe sobre a nova etapa do Programa de Controle de Emissões Veiculares - PROCONVE. DIÁRIO Oficial da União.

CARDOSO, L. D., MOREIRA, E. C. G., RANGEL, J. J. A. (2011). *Modelo de Simulação a Eventos Discretos para Análise de Inventário de Emissões de CO*. In: Simpósio de Engenharia de Produção, 2011, Bauru - SP. XVIII SIMPEP.

CARTWRIGHT, H. M. (1995). *The genetic algorithm in science*, Pesticide Science, 45, 171–178.

CHWIF, L.; MEDINA, A. C. (2010). *Modelagem e Simulação de Eventos Discretos, Teoria e Aplicações*. 3ª edição Ed. Bravarte.

COELHO, A. S., BRANCO, R. M. RODRIGUES, G. S. (2006). *Aprimoramento da produtividade de sistemas de manufatura e aplicação de algoritmos genéticos na solução de problemas de agrupamentos celulares*. Revista Produção Online, Florianópolis, Vol. 6, N .3, p.116.

COSTA, J. F. S. (2011). *A Genetic Algorithm to Obtain Consistency in Analytic Hierarchy Process.* Brazilian Journal of Operations & Production Management. Vol. 8, N. 1, pp. 55-64.

DAVIS, S.G. (1990). *Shedulling Economic lost size production runs*. Management Science, 36(8).

DIAGALAKIS, J. G.; MARGARITIS, K. G. (2001). *On Benchmarking Functions for Genetic Algorithms*, International Journal of Computer Mathematics, 1029-0265, 77 (4), p. 481 – 506.

FREITAS FILHO, P. J. (2008). *Introdução à modelagem e simulação de sistemas*. 2ª edição, Editora Visual.

FU, M. C. (2002) *Optimization for simulation: Theory VS. Practice*. Journal on Computing, vol. 14, n 3, 2002.

GOLDBERG, D. E. (1989). *Genetic Algorithms in search, optimization, and machine learning*. Reading. MA: Addison-Wesley.

HOLLAND, J. (1975). *Adaptation in natural and artificial systems*. The University of Michigan Press, Ann Arbor.

HUANG, Y., LI, Y. P., CHEN, X., BAO, A. M., ZHOU, M. (2010). *Simulation-based optimization method for water resources management in Tarim River Basin, China*. Procedia Environmental Sciences 2(0): 1451-1460.

IANNONI, A.P., MORABITO, R. (2002). *Análise do Sistema Logístico de Recepção de Cana-de-Açúcar: Um Estudo de Caso Utilizando Simulação Discreta*. Gestão e Produção, São Carlos, SP, V. 9, N. 2, P. 107-128.

IBGE. (22 de novembro de 2006). Produção Agrícola Municipal. Comunicação Social. Disponível em http://www.ibge.gov.br/home/presidencia/noticias/noticia_visualiza.php?id_noticia=740

KELTON, W. D.; SADOWSKI, R. P. E STURROCK, D.T. (2007). *Simulation with Arena*, Forth Edition, New York: McGraw-Hill.

LAW, A. M. (2007). *Simulation Modeling Analysis*. Fourth Edition, New York, Ed. MCGRAW-HILL.

MATTOS, V. L. D., BARBETTA, P. A., ANDRADE, D. F., SAMORYL, R. W. (2008). *Identification of Dispersion Effects in 2k Factorial Design*. Brazilian Journal of Operations & Production Management. Vol. 5, N. 2, pp. 73-91.

MANICOM, B., C. GREEN, C., AND W. GOETZ. (1993). *Methyl Soyate Evaluation of Various Diesel Blends in a DDC 6v-92 TA Engine*. Mississauga, Ontario: Ortech International.

MICHALEWICZ, Z. (1996). *Genetic Algorithms + Data Structures = Evolution Programs*. Springer-Verlag. New York, NY.

MONTGOMERY, D.C. (2009). *Design and Analysis of Experiments*. 7th edition. John Wiley & Sons, Inc.

MONTEVECHI, J. A. B., COSTA, R. F., LEAL, A., PINHO, A., (2010). Economic Evaluation of Scenarios for Manufacturing Systems Using Discrete Event Simulation Based Experiments. Brazilian Journal of Operations & Production Management. Vol 7, N. 1, pp. 77-103.

MONTEVECHI, J. A. B., LEAL, A., PINHO, A., COSTA, R. F., OLIVEIRA, M. L. SILVA, A. L. (2010). *Conceptual Modeling in Simulation Projects by mean adapted IDEF: an Application in a Brazilian company.* In: Proceedings of the Winter Simulation Conference, Baltimore, MD – USA. P. 1624 – 1635.

OLIVEIRA, J. F. G. de; ALVES, S. M. (2007). *Adequação ambiental dos processos usinagem utilizando Produção mais Limpa como estratégia de gestão ambiental.* Revista Produção, v. 17, n. 1, p. 129-138.

PEREIRA, M. A. CREPALDI, M. R., CALARGE, A. C. (2010). *A questão da sustentabilidade voltada ao desempenho organizacional: uma análise exploratória em empresas do setor sucroalcooleiro no Estado de São Paulo*. Exacta, São Paulo, Vol. 8, N. 3, p. 269-278.

PAGE, B. WOHLGEMUTH, V. (2006). *Combining discrete event simulation and material flow analysis in a component-based approach to industrial environmental protection*. Environmental Modelling & Software 21(11): P. 1607-1617.

PINHO, A. F. (2008). *Proposta de um método para otimização de modelos de simulação a eventos discretos.* Tese (Doutorado em Engenharia Mecânica) - Universidade Estadual Paulista Júlio de Mesquita Filho.

RANGEL, J. J. A., CUNHA, A. P., AZEVEDO, L. R., VIANNA, D. S. (2010). *A simulation model to evaluate sugarcane supply systems.* In: Proceedings of the Winter Simulation Conference, Baltimore, MD - USA. P. 2114-2125.

SARGENT, R. G. (2011). *Verification and validation of simulation models*. In: Proceedings of the Winter Simulation Conference, Phoenix, AZ – USA. P. 183 – 198.

SCHRIBER, T. J., BRUNNER, D. T. (2011). *Inside discrete-event simulation software: how it works and why it matters*. In: Proceedings of the Winter Simulation Conference, Phoenix, AZ – USA. P. 113 – 123.

WIDOK, A. H., WOHLGEMUTH, V. (2011). *Enhancing Event-Discrete-Simulation Software with Sustainability Criteria.* The Third International Conference on Advances in System Simulation. Barcelona – Spain. P. 190 – 195.

ZHOU, C. C., YIN, G. F., HU, X. B. (2009). *Multi-objective optimization of material selection for sustainable products: Artificial neural networks and genetic algorithm approach*. Materials & Design. Vol 30, N 4, Pages 1209–1215

ZHOU, X.; KUHL, M. E. (2009). *Sustainability toolkit for simulation-based logistics decisions.* In: Proceedings of the Winter Simulation Conference, Austin, TX – USA. P. 1466 – 1473.

ZHOU, X.; KUHL, M. E. (2010). D*esign and development of a sustainability toolkit for simulation.* In: Proceedings of the Winter Simulation Conference, Baltimore, MD – USA. P. 1601 – 1612.

ZHOU, X.; KUHL, M. E. (2011). *A sustainability toolkit for simulation: recent developments and future capabilities.* In: Proceedings of the Winter Simulation Conference, Phoenix, AZ – USA. P. 850 – 858.