Mathematical Modeling and Optimization of Downdraft Gasifiers Using Artificial Neural Networks (ANN) and Stochastic Programming Techniques

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Abstract. The research study explores the modeling and optimization of multi-objective operation of biomass gasification facilities using of Artificial Neural Networks (ANN) and Stochastic non-linear Programming methods. This study underpins the modelling by starting from the classification of the information derived from the systemic analysis of the gasification facilities. The study is based on the multi-objective mathematical modeling of these facilities through the different optimization and Neural Networks techniques specified in the literature. A 3^N experimental plan with 3 replicas is made to generate four models according to their performance indicators using Neural Networks, with satisfactory results and their evaluation based on regression of coefficients. The standard errors are calculated using biomasses with low, medium and high caloric power biomass. The experimental installation and the developed data acquisition systems are presented to validate the results. Numerical experimentation and the analysis show that such models could be used for developing operational system for existing design of downdraft installations.

Keywords: Biomass gasification · Renewable energy sources · Artificial Neural Networks · Processes operation

H. Ayaz and U. Asgher (Eds.): AHFE 2020, AISC 1201, pp. 375–384, 2021.
https://doi.org/10.1007/978-3-030-51041-1_50

1 Introduction

For the transformation biomass into energy, different technologies have been developed, motivated, basically, by the necessity of using the existing great quantity of wastes from the agricultural productive processes and domestic life [1], between these technologies the downdraft process became the most efficient way for electric power generation. In general, the rationality of the use of the technologies depends on the optimization of its operation. Given the inherent complexity of the gasification process and the necessity of modelling it operation, acquire particular interest the works linked to the simulation and optimization models linked to it operation [2]. Ahead, it is assumed as operation the tasks of decisions making associated to the selection of the variables values that determine the global efficiency of the process in real time, understanding as control the actions guided to achieve the previously adopted operation variables values [3]. Upon the development of the mathematical model for a given biomass processing system and its validation, the model can be utilized to predict or simulate the behavior and/or criteria and/or performance of the system. When it comes to simulating a complete flowsheet, due to its complexity involving hundreds of equations and variables, it is often advantageous to use process simulators to evaluate the process performance depending on different operating conditions in reasonable time with minimal effort [4]. Steady state simulators which can be used in simulating biomass gasification for hydrogen production could include ASPEN PLUS or other simulation package [5]. Another approach to simulate the behavior of some already designed downdraft installations could be the organization of experimental plans, on the basis of system analysis, and the processing of the obtained results by regression or neural network models [6, 7].

In the present work neural network models (ANN) for a concrete downdraft installation lodged by low, medium and high caloric power biomasses are found starting from an applied system analysis that allows to define the set of relationships required to model it operation in real time [7, 8]. A 3^N experimental plan with three replicas was organized, from which four ANN models, corresponding to the respective performance indicators, were elaborated with satisfactory results from their evaluation based on the calculated regression coefficients and standard errors for eichhornia crassipes (commonly known as lechuguin), oryza sativa (rice straw) and wood, used as biomass in an experimental installation with the objective of generating the experimental data required to identify the relationships that should be part of the stochastic non-linear decisions making operation models. Bellow the results obtained for the rice straw biomass modelling, the algorithm used for solving the obtained model and the human-machine interaction procedure are described.

2 System Analysis

The proposed methodology contributes to the literature in the field of systems analysis aiding to make easier and better engineering decisions. The solution of these tasks includes components, either as the solution of the complex tasks, its decomposition and the solutions composition among the resulting tasks and/or the conciliation of interrelated criteria [3]. This methodology is explained bellow in the example of the studied task. The external analysis is constituted by the following stages (see Fig. 1).

Study of the overall task and determination of coordination variables. In this study, the specification of the higher-level system and the analysis of the coordination variables are performed. In this way, one makes sure that the system under analysis is appropriately inserted in the "environment" in which it will work. The coordination variables "*u*" is related to the overall task. In the operation of downdraft installations, the more span level system is constituted by the existent energy system in the isolated from the national electric net territory as a part of which the downdraft installation is considered.

Related coordination variables

- Demanded (or desirable) power u^d.
- Lower level of the caloric power required of the generated gas PCG^{inf}.
- Masa and type of available biomass to be used $Cbio_j^{sup}$, j ∈ (1, 2, …, *n*).

The input data "*d*" of the studied task is constituted by the current value of the environmental humidity *Hu*. Efficiency indicators "*y*". These indicators determine the overall behavior and the quality of the system. They could be formalized in a quantifiable or non-quantifiable way. In the studied case were obtained the following quantifiable indicators: Generated power *u*, that is determined by the caloric power *PCG* y the mass flow of the gas *MG*. Installation efficiency *Ef*. And the Temperature of the pyloric zone *Tzp*. The decisions variables "*x*" is those that could be modified by the system user with the purpose of obtaining the best possible commitment among the efficiency indicators. This compromise is determined, among other things, by the relative importance that the user donates to each indicator. In the studied case it was obtained:

- Masa of the biomass *j* type $Cbio_j$, $j \in (1, 2, \ldots, n)$
- Mass flow of the combustion air *Cau*

Elaboration of the conceptual mathematical model for the decision support process. Starting from the analysis of the considered engineering task, the set of quantifiable indicators to be optimized is defined along with the set of intermediate variables subject to restrictions and the set of indicators of subjective character to evaluate. In this way, it becomes possible to formulate the conceptual model for organizing a decision support process. In this model the simulation, visualizations, and the results of human-machine interaction are incorporated.

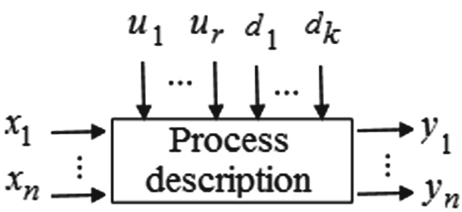

Fig. 1. Classification of the information involved in the preparing a decision support process

Conceptual mathematical model for the decision support process. Starting from the analysis of the considered engineering task, the set of quantifiable indicators to be optimized is defined along with the set of intermediate variables subject to restrictions and the set of indicators of subjective character to evaluate. In the studied case will be:

$$Minimize\left\{\max\left[w_1\frac{\left|Ef - Ef^d\right|}{Ef^d},(1-w_1)\frac{\left|u-u^d\right|}{u^d}\right]\right\} \tag{1}$$

Assuring the fulfillment of:

$$Cbio \leq Cbio^{sup} \tag{2}$$

$$Tzp(Cau, Cbio, Hu) \geq Tzp^{inf} \tag{3}$$

$$PCG(Cau, Cbio, Hu) \geq PCG^{inf} \tag{4}$$

Where:

$$u = MB\,(Cau,\ Cbio, Hu) * PCG\,(Cau, Cbio, Hu) \tag{5}$$

In the relationship (1) coefficient w_1 represents the "importance level" the indicative *Ef* it values varies in the interval 0–1. The optimization model's solution, according to external analysis, requires the identification of the following relationships.

$$Ef = Ef\,(Cau, Cbio,\ Hu) \tag{6}$$

$$Tzp = Tzp\,(Cau, Cbio,\ Hu) \tag{7}$$

$$MG = MG\,(Cau,\ Cbio,\ Hu) \tag{8}$$

$$PCG = PCG\,(Cau,\ Cbio,\ Hu) \tag{9}$$

The internal analysis consists on the identification of the models required for the calculation of all and each one of the acting indicators represented by the expressions (6)–(8). As it comes off from analysis of the state, reflected in the literature, of the processes modelling and simulation methods for the operation of downdraft type gasifiers, briefly carried out in the introduction, the models identification could be done starting from experimental plans and its later prosecution to obtain models that satisfactorily identify the relationships (6)–(8). With this purpose, an experimental plan was conceived with 3 replicas structure that allow to reflect the casual caused errors, including the mensuration ones, for biomasses with low, medium and high caloric power. As such biomasses were selected: Eichhornia Crassipes (popularly known as lechugín), Oryza sativa (rice straw) and firewood. In the Table 1 are exposed technical characteristics of the downdraft gasifier selected for doing experiments. In Table 1 the more important technical characteristics of the installation selected for experimentation are shown.

Table 1. Technical characteristics of the dowdraft gasifier used for experimentation

Parameter	Values
Max. electric power (KW)	10
Gas flow (m^2/hr)	0.5–27
Consume of biomass (kg/day)	10–320

The experiments were carried out by lots in the following order: activation of the installation, biomass loading, opening of the air valve, capture of the resulting gas and sending to laboratory for the gas's composition and mass measurement and calculation of its caloric power by the authors. The temperature measurement was carried out in a permanent way in the points indicated in the Fig. 2, and averaged for the pyloric area for the whole lot. In the articles [7–9] the authors and their collaborators published the detailed experimental data, non-linear regression and neural network models results obtained for identifying the relations (6)–(9).

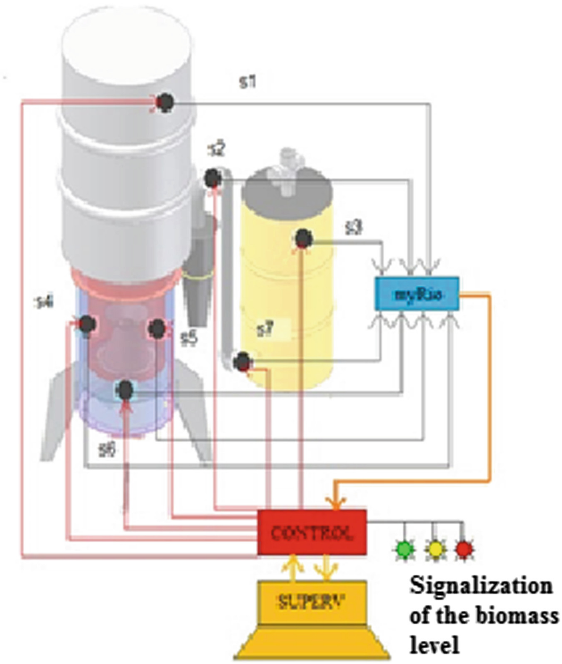

Fig. 2. Control points of the downdraft gasifier

Best results were obtained by artificial neural network modelling. The optimal number of nodes found, in all the cases, were 8 for the first hidden layer and 4 for the second hidden layer. The best transfer function found for the layers 1–3, for all the biomasses was the sigmoidal tangent function. For all the relations and feeding biomasses in each one and all the biomasses the more appropriate structure of the models is shown in the Fig. 3.

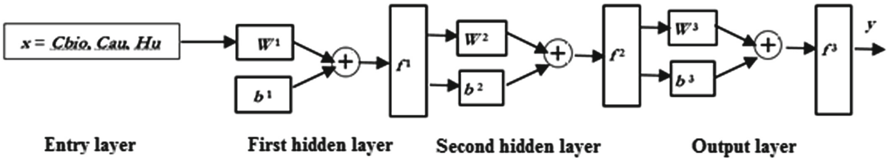

Fig. 3. Structure of the neural network found for all the biomasses and all the outputs

So, the models found for all the biomasses an all the outputs have the general mathematical structure:

$$y = f^3\left(W^3 f^2\left(W^2 f^1\left(W^1 x + b^1\right) + b^2\right) + b^3\right) \tag{10}$$

Where y is the output vector, x the input vector W^i, f^i, b^i coefficients` matrixes, transfer functions and bias vectors of the i layer.

3 Synthesis of the Operation System

Given the stochastic character of the real values around the calculated by the ANN model, the real values the calculated by the models (2.6)–(2.9) magnitudes are distributed around its calculated values by close to normal distribution [10]. As it is required to assure close to desirable values, with certain probability, of the efficiency and of generated power, assuring the restricted values of the interest variables *Cbio*, *Tzp* and *PCG*, the optimization model (1)–(5) it is expressed in the following way

$$Minimize\left\{\max\left[w_1\frac{\left|A_h(Ef) - Ef^d\right|}{Ef^d}, (1 - w_1)\frac{\left|A_h(u) - u^d\right|}{u^d}\right]\right\} \tag{11}$$

Where:

$$u = MG(Cau, Hu.\, Cbio) * PCG\left(Cbio_{j,} Cau, Hu\right) \tag{12}$$

assuring:

$$Cbio_j \leq Cbio_j^{sup};\ j = 1, \ldots, jt \tag{13}$$

$$A_h[Tzp(Cau, Hu, Cbio)] \geq Tzp^{inf} \tag{14}$$

$$A_h[PCG(Cau, Cbio, Hu)] \geq PCG^{inf} \tag{15}$$

Where A_h is the assured value of the corresponding magnitude, with a probability higher or similar to h. Given the normal character of the behavior of the evaluated indicators with helped by regression equations (including those obtained by neural nets), with regard to its calculated values, each assured value you could be calculated by the expression [10]:

$$A_h(Ind) = Ind_c - Perc_h S \tag{16}$$

For a probability h = 95%,

$$A_h(Ind) = Ind_c - 1{,}68\, S \tag{17}$$

In the case of the indicators *Ef, MG*, *Tzp* and *PCG* the value of the S parameter is the same of the corresponding equation of selected regression ANN, because the realization of 3 replicas in the experiments leads to the integration of the dispersion of the measurements it is included in common *S* value of. The parameters of the distribution of the indicator *u* are distributed starting from the corresponding parameters of the distributions of *MG* and *PCG* according to [10]:

$$\overline{u} = \overline{MG} \times \overline{PCG} \tag{18}$$

$$S_u = \sqrt{S_{MG}^2 + S_{PCG}^2} \tag{19}$$

Where $\overline{MG}, S_{MG}, \overline{PCG}, S_{PCG}$ are the means calculated values and the dispersion obtained during the calculation of *MG* and *PCG* helped by the neural network corresponding to the biomass used. In spite of the stochastic character of the model (1)–(5), their identification and conversion to the model (10)–(14) with the inclusion of the relationships that assure certain probabilities of the indicators that are part of the model transform it into a non-lineal programming model. The procedure for the optimization of the operation the Exploration in a Net of Variables method of Non-Lineal Programming (PNL) was selected. This way, the following solution outline is implemented: Reading of type of biomass to be gasified (corresponding to own indicators description models) $Cbio_j^{\mathrm{sup}}, Tzp^{inf}$, PCG^{inf}. Settle down the initial and final intervals of the two decision variables: $Cbio_j$ from zero until $Cbio_j^{\mathrm{sup}}$ and *Cau* from zero until Cau^{sup}. The four cutting points corresponding to the four combinations of internal values of both variables are generated. The objective function (10) is calculated for the four combinations adding a penalization function for the nonfulfillment of the restrictions (12), (13) and (14).

The combination is selected with smaller value of the penalized objective function and the subinterval that doesn't contain the component of the best solution for each variable is eliminated and Cau and $Cbio_j$ superior or inferior values are rectified as it proceeds. Return to the beginning of the exploration cycle while the search longitude of at least one of the variables adopts a smaller than the adopted precision value (0, 1) for Cau and $Cbio_j$. For the implementation of the penalization of the objective function for the nonfulfillment of the restrictions of the task the J. N. Kelley function is applied [3]. For this, the following it easier expressions are used:

$$P_{Cbio} = 10^8 (Cbio - Cbio^{required})^2 \tag{20}$$

$$P_{TCraq} = 10^8 (A_{0,95}(Tzp) - Tzp^{craq})^2 \tag{21}$$

$$P_{PCR} = 10^8 (A_{0,95}(PCG) - PCG^{required})^2 \tag{22}$$

The original objective function is substituted by:

$$Z' = Z + P_{Cbio} + P_{TCraq} + P_{PCR} \tag{23}$$

The Pareto front obtained, for rice straw biomass, using concrete input data are shown in Fig. 4.

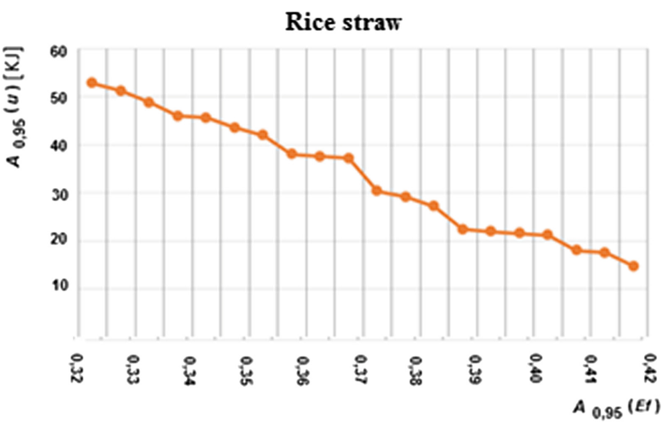

Fig. 4. Pareto front obtained loading rice straw biomass

Similar fronts were also obtained for the eichhornia crassipes and firewood biomasses.

4 Conclusions

The detailed study of the state of the art evidences the lack of a systemic approach in the construction of operation models of downdraft installations, being arrived only to the elaboration of certain rules in determinate technologies variants and the modeling and characterization of the syngas obtained, that are used for the realization of simulations that are validated with data reported by designers or other authors. In the last years could be observed the evolution of the mathematical tools and of more modern software used. The systemic analysis constitutes an indispensable requirement for the elaboration of conceptual models of the processes of operation of the downdraft gasification installations. These models must be identified posteriorly to obtain applicable mathematical models for the process operation. The systemic study allows to elaborate experimental plans and the characteristics of needed installations for doing it, with the due instrumentation and the localization of the control points, previous to the realization of the experimental design and the prosecution of data for the identification of the obtained conceptual mathematical model. From the research carried out it is clear the usefulness of the multilayer artificial neural networks or non-lineal regression techniques in the construction of operation models of the gasification processes in downdraft installations. The later exploitation of the installation could allow to complete the primary information to perfect and to increase the precision of these model and, therefore, the same quality of the operation these installations. The elaboration of behavior rules for the operation of facilities of gasification type downdraft facilitates its automation in the same PLC implemented for the control, without additional material cost some, although to coast of the increment of the error of determination.

Acknowledgements. We would like to acknowledge SMME-National University of Sciences and Technology (NUST), Islamabad, Pakistan, Studies Center of Mathematics for Technical Sciences - (CEMAT), Universidad Tecnológica de La Habana, "Jose Antonio Echevarria" (CUJAE), Habana, Cuba and Laboratorio de Energía Renovable, Universidad de las Fuerzas Armadas del Ecuador (ESPE), Quito, Ecuador for providing necessary support and facilities to conduct this study.

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