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# Quantitative Analysis for Biomass Energy Problem Using a Radial Basis Function Neural Network

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# RBF 뉴럴네트워크를 사용한 바이오매스 에너지문제의 계량적 분석

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In biomass gasification, efficiency of energy quantification is a difficult part without finishing the process. In this article, a radial basis function neural network (RBFN) is proposed to predict biomass efficiency before gasification. RBFN will be compared with a principal component regression (PCR) and a multilayer perceptron neural network (MLPN). Due to the high dimensionality of data, principal component transform is first used in PCR and afterwards, ordinary regression is applied to selected principal components for modeling. Multilayer perceptron neural network (MLPN) is also used without any preprocessing. For this research, 3 wood samples and 3 other feedstock are used and they are near infrared (NIR) spectrum data with high-dimensionality. Ash and char are used as response variables. The comparison results of two responses will be shown.

Keywords : Biomass, Gasification, Radial Basis Function Neural Network, Principal Component Regression, Multilayer Perceptron Neural Network

## 1. Introduction

The use of biomass as an energy feedstock is emerging as a potentially viable alternative to address U.S. energy security concerns, foreign oil dependence, rural economic development, and diminishing sources of conventional energy. Biomass (organic matter that can be converted into energy) may include food crops, crops for energy (e.g., switchgrass or prairie perennials), crop residues, wood waste and by-products, and animal manure [4]. There are three reasons why the biomass is increasingly demanding. They are conventional fossil energy makes pollutions, excessive agricultural products and rural development. For the biomass gasification process, quantitative analysis is done in this article to measure efficiency of biomass product. To measure biomass efficiency, near infrared (NIR) spectrum is used.

Since NIR is a rapid, cost-effective, non-destructive, and efficient analytical method. The interest in NIR spectrospecopy lies in its advantages over alternative instrumental techniques. Thus, it can record spectra for solid and liquid samples with no pretreatment, implement continuous methodologies, provide spectra quickly and predict physical and chemical parameters from a single spectrum. These attributes make it especially attractive for straightforward, speedy characterization of samples [3]. The spectral data have remark-

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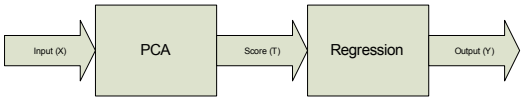
able characteristics, which make necessary their treatment by specific methods. The data maybe comprised of more variables than observations [2].

For the methodology viewpoint, spectral data needs data transformation methods to handle high dimensionality. There are various data transformation techniques such as singular values decomposition (SVD), principal component analysis (PCA), independent component analysis (ICA), wavelet transform (WT), and Fourier transform (FT).




<Figure 1> Principal Component Regression Model

After transformation, the data mining approaches are applied to the transformed data for modeling. In some cases, the spectral data and the target property are not linearly related as a result of instrumental factors or the physico-chemical nature of the sample. These cases can be addressed by using non-linear calibration methods, particularly artificial neural network [3]. Neural networks are not the only tools to handle non-linear multivariate data. However, their flexibility is often a decisive asset compared with parametric techniques that require the assumption of a specific hard model form. Hard models cannot be developed with NIR data due to the significant overlap of combination and overtone bands in the spectra [5].

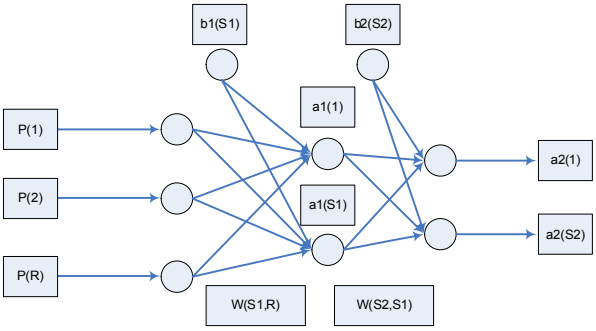
In section 2, the methodologies are presented. Experiments and results are described in section 3. This article is concluded in section 4.

## 2. Methodology

### 2.1 Principal Component Regression

The principal component regression (PCR) methodology [8] consists of two steps. The first step is principal component analysis (PCA) [6]. The second step is a regression model constructed by minimizing sum of square error between predicted and original response.

The principal component analysis (PCA) will be used to reduce the dimension without losing any important information. The PCA will use the maximum variance technique to choose better principal component, and normalize each




<Figure 2> Multilayer Feed-Forward Neural Networks

principal component and orthogonality of each principal component. Using the PCA, the collinearity will be removed.

The PCA term is $\mathbf{T} = \mathbf{XP}$ where $\mathbf{T}$ is a score matrix $(m \times k)$, $\mathbf{X}$ is an original matrix $(m \times n)$, and $\mathbf{P}$ is a loading matrix $(n \times k)$.

For example, $m$ = 3, $n$ = 3 and $k$ = 2 then,

$$\begin{pmatrix} t_{11} & t_{12} \\ t_{21} & t_{22} \\ t_{31} & t_{32} \end{pmatrix} = \begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{pmatrix} \times \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \\ p_{31} & p_{32} \end{pmatrix}$$

The procedure of PCR is shown in <Figure 1>. The strength of PCR is not only the transformation of lower dimensional subspace but also the prevention for over-fitting the data since possible regression function is restricted.

### 2.2 Multilayer Perceptron Neural Network (MLPN)

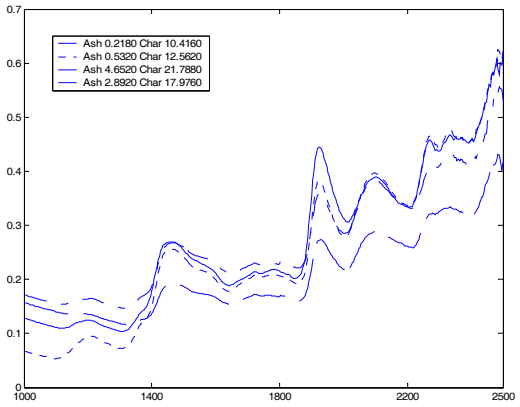
There are three layers of neurons in MLPN process [1], which are input, hidden and output layers. The inputs pass through the input layer to hidden nodes. The hidden layer multiplies the inputs by weights, sums them, and operates on the sum with a function such as a sigmoid or tangent sigmoid one. The result is passed to each output nodes when there is a hidden layer. The output layer multiplies the inputs by weights, sums them and operates on the sum with a function such as a linear one. The result is the output. The hidden layer and output layer can have either linear or non-linear function. The activation function is needed to be continuous, monotonically increasing, and differentiable. The activation function signals propagate forward and error signals propagate backward through the network. <Figure 2> shows architecture of typical three-layer feed-forward multilayer perceptron network.

### 2.3 Radial Basis Function Neural Network (RBFN)

The radial basis function neural network [7] has two layers, which are hidden and output layer. The activation function of hidden layer is the radial basis function called the Gaussian activation function, which is a non-linear and local mapping layer. The activation function of output layer is the standard linear function and performs a linear transformation of the output of hidden nodes.

The Gaussian Activation Function is as follows :

$$f_x(\mathbf{x}) = \exp\left[-\frac{\|\mathbf{x}-\boldsymbol{\mu}\|^2}{\sigma_i^2}\right]$$




<Figure 3> NIR Spectra with Ash and Char Contents

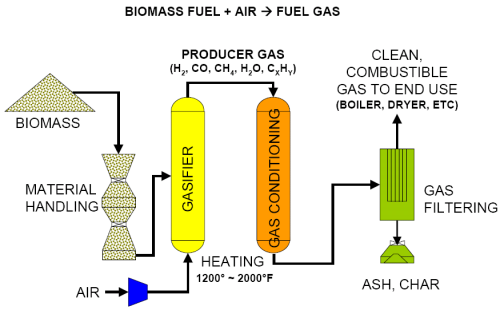
where $\mathbf{X}$ is the input vector, $\boldsymbol{\mu}$ is the center of a region called a receptive field, $\sigma_i$ is the width of the receptive field and $f_i(\mathbf{X})$ is the output of the $i^{th}$ neuron.

## 3. Experiments

### 3.1 Data Description

Three wood samples; red oak, yellow popular, hickory and three other biomass feedstock; switch grass, corn stover and bagasse are selected and used for this experiment. Wood samples are collected from different trees. Switch grass are collected in different location as same as corn stover. There are 54 samples and 375 variables (wavelengths). In <Figure 3>, the NIR spectrum is shown. The samples are divided into training (27 odd number samples) and test sets (27 even number samples).

Ash and char contents are used as response variables. Ash content measurement was conducted based on the method (similar to ASTM standard method, E1755-01) recommended by National Resources and Energy Laboratory (NREL). Simply described, appropriately marked crucibles were placed in the muffle furnace at 575 ± 25°C for four hours. Then they were taken out them directly into a desiccator, cooled down to room.




<Figure 4> Example of Biomass Gasification [9]

Temperature weighed to the nearest 0.1mg. Again, the crucibles were placed back in the muffle furnace at 575 ± 25°C and dried to constant weight. Constant weight is defined as a less than ± 0.3mg change in the weight upon one hour of re-heating the crucibles.

Oven-dried biomass samples at 105°C weighed about 1.5g and placed into the tared crucible. Then an ashing burner burned the samples until no more smoke or flame appeared. The burned samples were placed in the muffle furnace for 24 ± 6hours. Then the crucibles were removed from furnace directly into a desiccator and weighed to the nearest 0.1mg. Again, the samples were placed back to the furnace, ashed to constant weight, and cooled down to room temperature in desiccator.

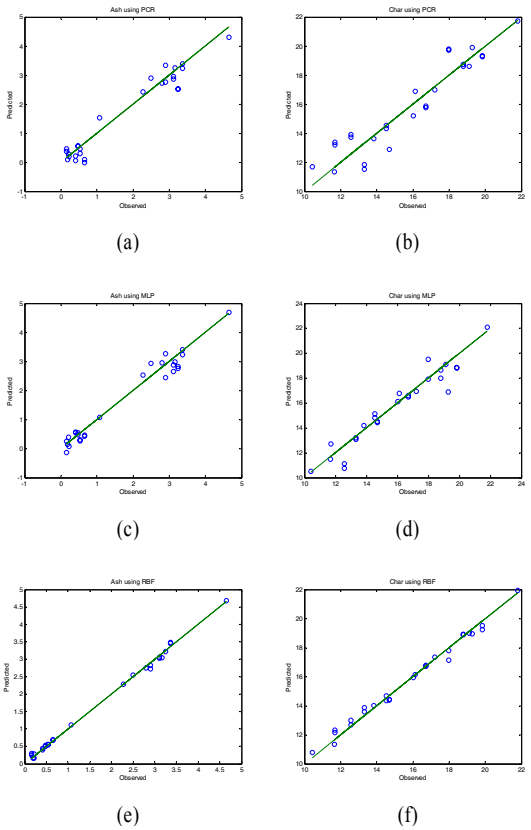
Char content were measured by using thermal gravity analysis (TGA) (Perkin-Elmer Pyris 1 TGA). Samples of 6-7 mg were first heated from 50°C to 105°C at a rate of 25 °C min-1 and kept at 105°C for 10 min to remove the moisture. Then samples were heated again to 750°C at the same heating rate under nitrogen atmosphere (flow rate of 20 mL min-1). Char content was calculated from the final weight loss at 750°C by using the initial weight of sample without moisture content. <Figure 4> displayed an example of biomass gasification. As shown in <Figure 4>, the by-products of a gasification process are ash and char. When the efficiency of the by-products is known before gasification, there are many benefits such as cost.

### 3.2 Experiment Results

For the experiments, a training set used for a modeling and a test set used as the validating without cross-validation. Mean squared errors are obtained with a test set.

With over 1% variance, principal components were collected and transformed for principal component regression. In this experiment, 9 principal components was collected and used for prediction.

For the multilayer perceptron neural network, it needs exhaustive computational time. Input variables were transformed with principal component transform. After that, the transformed input data underwent feed-forward back-propagation with the multilayer perceptron neural network. As same as principal component regression, 9 principal components were used for the multilayer perceptron neural network. For the hidden and output layer function, tangent sigmoid and linear functions were used. 2 responses were used as output and 4 hidden neurons were used in the multilayer perceptron neural network.




<Figure 5> Predicted vs. Observed Plots : (a) Ash with PCR (b) Char with PCR (c) Ash with MLPN (d) Char with MLPN (e) Ash with RBFN (f) Char with RBFN

<Table 1> Spread Constants Selection in Radial Basis Function Network

| Spread Constants | 13 | 14 | 15 | 16 | 17 |
|---|---|---|---|---|---|
| Ash | 0.0056 | 0.0042 | 0.0050 | 0.0042 | 0.0085 |
| Char | 0.1327 | 0.1439 | 0.1142 | 0.1649 | 0.1989 |

<Table 2> Mean Squared Error

| MSE | Training | | Test | |
|---|---|---|---|---|
| | Ash | Char | Ash | Char |
| PCR | 0.0482 | 0.6864 | 0.1113 | 1.2019 |
| MLPN | 0.0124 | 0.0400 | 0.0639 | 0.9340 |
| RBFN | 0.0000 | 0.0025 | 0.0050 | 0.1142 |

In radial basis function neural network, the network modeling was fast even though, the variables were larger than the samples. As seen in <Table 1>, 15 spread constants were selected and gave least mean squared error of test set for the Gaussian activation function. For the hidden layer, 22 neurons were used. 375 variables were used as input and 2 responses were used as output.

For the performance measure, mean squared error (MSE) was used. As shown in <Table 2>, the smallest mean squared error of ash and char contents for prediction of training data were found by RBFN. Also, for prediction of the test set, the smallest mean squared error for both ash and char contents were collected from RBFN. From the <Figure 5>, the graphical representations were provided for test set.

## 4. Conclusion

RBFN was used to forecast energy efficiency of biomass and compared with the PCR and the MPNN. The conventional regression could not be used in the high-dimensional case due to the bigger size of variables compared to observations. The PCR was applied with a principal component transform in the first stage and ordinary regression was applied in the second stage. For the MPNN, the network was constructed after transform because of exhaustive computational problem. 9 principal components were used for the PCR and the MPNN. As shown in <Table 2>, the MPNN showed the better results than the PCR. Even if the MPNN used same number of principal components as the PCR, the performance showed better results.

For biomass efficiency prediction, the best method is the RBFN which gave the smallest mean squared error for the prediction of test set. From the above results, it is easier to conclude that the RBFN can be suitable approach for energy-efficiency forecasting in biomass application areas with NIR spectrums.

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