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Neuro-Fuzzy Soft Sensor Estimator for Benzene Toluene Distillation Column

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Abstract

The distillation is widely used separation technique in oil and gas refineries. Accurate measurement of the composition of separated constituents is necessary to estimate the purity of the products. Composition measurement using online analysers causes process delay and requires large initial investment. As a solution to this problem, soft sensor estimators can be used to determine the composition of separated product. In this work soft sensor estimators are used for predicting top and bottom compositions in benzene toluene distillation column. More sensitive tray temperatures, re-boiler duty and reflux rate (measured variables) of distillation column were used to predict top and bottom composition (unmeasured). Data used for soft sensor based estimation are generated using process simulation software HYSYS. NARX based ANFIS algorithm was proposed for soft sensor modelling. In this method, most influential inputs for soft sensor modelling were selected using exhaustive search. Neural network model and ANFIS model are also compared using statistical criteria like root mean square error and correlation coefficient (R^2) values. It has been shown by the results that ANFIS performs better while comparing neural network method and ANFIS with the same number of iteration.

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Keywords: Distillation; ANFIS; NARX; Soft Sensor; HYSYS

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1. Introduction

More than 95% of liquids in the industry are separated by distillation [1]. High purity of the separated product is required for delivering good quality products. Moreover, distillation column product composition should be kept near the set point. Moreover, distillation column product composition should be kept near the set point of product composition even though in the face of upsets due to disturbances in the feed or change in feed composition[2]. Hence, composition measurement of delivering products is necessary. The real time measurement of the composition measurement is a challenging, difficult problem in distillation [3]. This can be done using online product analyzers or offline analyzers in laboratory [4]. But this method is rarely used because it results in large measurement delay, sampling delay and high investment cost of online analyzers [2]-[5]. Control action also delayed due to delay in measurement and product quality is also affected subsequently [6]. Delays in order of hours often are acquired, and information regarding the composition cannot be used as the feedback signal in laboratory measurement [4]. Proper maintenance and calibration of the equipment like chromatograph are also required for measurement of this type [6]. These limitations affect the quality of the products. Large numbers of this type of expensive analyzers are also to be used if many processes streams are involved in distillation [7].

Nomenclature

$u_1(t)$	Reboiler Temperature	$u_4(t-1)$	Delayed Condenser Temperature
$u_1(t-1)$	Delayed Reboiler Temperature	$u_5(t)$	Reflux rate
$u_2(t)$	Second Tray's Temperature	$u_5(t-1)$	Delayed reflux Rate
$u_2(t-1)$	Delayed Second Tray's Temperature	$y_1(t)$	Top Composition
$u_3(t)$	Tenth Tray's Temperature	$y_1(t-1)$	Delayed top composition
$u_3(t-1)$	Delayed Tenth tray's Temperature	$y_2(t)$	Bottom Composition
$u_4(t)$	Condenser Temperature	$y_2(t-1)$	Delayed Bottom Composition

As a solution to the expensive online measurement or offline laboratory measurement, the soft sensors (an association between sensor hardware and estimator software) can be used as an alternate for composition measurement [2]-[7]. Soft sensors were derived from two words "software" and "sensors". The word "software" means that soft sensor models are developed using computer program whereas the word "sensor" means that model was used for giving the same information as their hard ware counter parts were used [8]. Soft sensors are used to measure the unmeasured quantity (primary variable) from measured quantity (secondary variable). Temperature, pressure, and liquid levels etc. are used as the sensing variable in process or chemical industry [5]. Two types of soft sensors are used, i.e., model driven and data driven soft sensor. Model-driven soft sensors also called as a phenomenological model are based on first principle model whereas data-driven soft sensors are based on measured data within plants [4], [8]. Data-driven soft sensors achieved popularity comparing with model driven since it is mainly depended on actual process and can represent the actual process more accurately [8]. Product qualities (primary variable) such as compositions are predicted from the linear combination of process inputs and outputs (secondary variables) [2] using the soft sensor. In the distillation column, composition measurement can be achieved modeling a soft sensor using the primary variable as trays, reboiler and condenser temperatures, heat duty and reflux rate [6].

Data-driven or empirical soft sensor models usually used to estimate product composition in distillation columns are artificial neural network models, Kalman filters, fuzzy models, adaptive network-based fuzzy inference system (ANFIS) models and support vector machine (SVM) models. In [9], 11 tray temperatures were used to estimate the dual composition using partial least square (PLS) method. Artificial neural network models were used as soft sensor estimators in [2], [5], [10], [11]. In [2], [5], [11], distillation column top and bottom product compositions were predicted using artificial neural network. Compositions were predicted in [11] using empirical neural network model based on the steepest descent algorithm where tray temperatures were used as the primary variable whereas in [2], Leven-Berg Marquardt based neural network model was used as soft sensor model where tray temperatures along with reflux rate and heat duty were used as the primary variable. Better performance was achieved using soft sensor model in [2] comparing with software sensor model [11]. Support vector machine based