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## PRIMJENA SOFTVERSKOG ANALIZATORA U UNAPREĐENJU KVALITETE PROIZVODA I VOĐENJA PROCESA HIDRODESULFURIZACIJE

### Sažetak

Sve stroži zahtjevi kvalitete proizvoda zahtijevaju konstantnu potrebu održavanja i unapređenja kvalitete proizvoda. U tu je svrhu nužno opremiti postrojenja procesnim analizatorima. Posljednjih se godina u industrijskim postrojenjima sve više primjenjuju softverski analizatori, zbog svoje cijene i pristupačnosti i zbog brze i pouzdane primjene. Njihov rad temelji se na primjeni matematičkog modela u kontinuiranoj procjeni fizikalno-kemijskih svojstava ili kemijskog sastava. Primjenjuju se kao zamjena i nadopuna hardverskim procesnim analizatorima i laboratorijskim analizama, u samostalnoj primjeni za određivanje fizikalno-kemijskih svojstava ili kemijskog sastava, u unapređenju motrenja i vođenja procesa, te pri primjeni naprednog vođenja.

Ovim radom istražena je mogućnost primjene softverskog analizatora za određivanje sumpora u proizvodu procesa hidrodesulfurizacije, lakom plinskom ulju, a postignuti rezultati istraživanja primijenjeni su i u praksi.

### Uvod

Eksperimentalni podaci i mjerenja s industrijskih postrojenja primjenom različitih metoda analize procesa mogu biti korišteni u svrhu promatranja i vođenja procesa i u svrhu razvoja modela i određivanja pojedinih parametara procesa. Zbog zahtjeva kvalitete goriva i potrebe za boljim vođenjem procesa, potreba preciznog mjerenja procesnih veličina i fizikalno-kemijskih svojstava svakim je danom sve veća. Posljednjih godina u procesnoj su industriji uz neizostavne hardverske procesne analizatore sve više prisutni i softverski analizatori (engl. software sensors, software analyzers). Softverski analizatori temeljeni su na matematičkom modelu koji omogućava kontinuiranu (engl. on-line) procjenu fizikalno-kemijskih svojstava i

kemijskog sastava. Svoju primjenu nalaze u samostalnom radu, ali i kao nadopuna klasičnim hardverskim procesnim analizatorima.

Softverski analizatori mogu biti temeljeni na matematičkom analitičkom modelu kojim se primjenjuju fizikalno-kemijski zakoni, na statističkim metodama (engl. data mining) ili na metodama primjene umjetne inteligencije, tj. neuronskih mreža. Primjena analitičkih modela postaje ograničena kad je proučavani sustav kompleksniji. Zbog kompleksnosti sustava u procesnoj industriji za izradu analitičkih modela potreban je osim znanja i velik broj eksperimentalnih podataka, te nerijetko duga eksperimentalna istraživanja. Zbog toga se za primjenu softverskih analizatora najčešće koriste matematički modeli temeljeni na neuronskim mrežama.

## Primjena softverskih analizatora

Neuronske mreže danas u svijetu nalaze široku primjenu u investicijskim analizama, u forenzičnim analizama, u vođenju i motrenju procesa, sa svrhom otkrivanja pogrešaka i kvarova u zrakoplovnoj, željezničkoj i drugim industrijama i sl. U procesnoj industriji jedna od najčešćih primjena neuronskih mreža je u svrhu izrade softverskih analizatora.

Primjena softverskih analizatora temeljenih na neuronskoj mreži može biti slijedeća:

1. Primjena pri nadopuni i zamjeni hardverskih procesnih analizatora i laboratorijskih analiza.

Prilikom redovitih servisiranja uređaja ili njihovog kvara, softverski analizator nastavlja provoditi analizu svojstava na temelju matematičkog modela i povijesnih procesnih podataka koji su omogućeni dotadašnjim radom hardverskog analizatora. Osim toga, hardverski analizatori daju rezultat analize svakih 10-15 minuta, dok je softverski analizator u mogućnosti prikazati rezultat i svake minute. Paralelnim radom, softverski analizator nerijetko može ukazati i na pogrešku koju proizvodi hardverski.

2. Primjena u samostalnom određivanju fizikalno-kemijskih svojstava ili kemijskog sastava.

Softverski analizatori mogu raditi u samostalnom određivanju fizikalno-kemijskih svojstava ili kemijskog sastava ako ne postoji hardverski analizator, a laboratorijske analize se provode nekoliko puta dnevno. Jedna od čestih primjena pri samostalnom korištenju jest pri određivanju emisije plinova kao i detekcije izvora štetnih plinova čime se zamjenjuju skupi uređaji.

3. Primjena pri unapređenju motrenja i vođenja procesa.

S obzirom da sve točke s distribuiranog kontrolnog sustava mogu biti dio matematičkog modela neuronske mreže, procesne podatke moguće je koristiti u svrhu boljeg vođenja procesa, za detekciju problema i kvarova, određivanje uskih grla procesa, optimizaciju procesa i sl.

4. Primjena uz napredno vođenje procesa.

Glavni cilj primjene naprednog vođenja procesa je povećanje iscrpaka i kvalitete proizvoda, a tu je funkciju nemoguće obaviti bez velikog broja analizatora. Kako za određivanje mnogih svojstava nisu nužni hardverski procesni analizatori kojima je cijena nerijetko i viša od cjelokupnog projekta, svojstva se mogu određivati softverskim analizatorima.

Primjeri konkretne primjene softverskih analizatora temeljenih na neuronskoj mreži su sljedeći:

- određivanje fizikalno-kemijskih svojstva proizvoda kao npr. vrelište, plamište, krutište, tlak para, iscrpaci, kemijski sastavi, oktanski brojevi, itd.
- određivanje emisija plinova,
- matematičko modeliranje destilacijskih kolona s određivanjem kemijskih sastava vrha i dna kolona, određivanje iscrpaka kolona,
- matematičko modeliranje reaktora,
- procjena rada i onečišćenja stijenki izmjenjivača topline i sl.,
- ekonomske procjene.

Prednosti softverskih analizatora s primijenjenom neuronskom mrežom su sljedeći:

1. Nije potreban velik broj parametara kao ni provođenje dugotrajnih eksperimentalnih istraživanja.

Da bismo postavili analitički model reaktora npr. procesa hidrodiesulfurizacije nužna su dugoročna eksperimentalna istraživanja koja uključuju i analizu laboratorijskog reaktora. Također, potreban je velik broj parametara koje je često nemoguće eksperimentalno odrediti, a nisu dostupni ni u literaturi. Postavljanje matematičkog modela temeljenog na neuronskoj mreži rješenje je za navedene probleme jer se zasniva na povijesnim podacima konkretnog reaktora.

2. Mogućnosti pojednostavljivanja složenih nelinearnih sustava, nerješivih klasičnim metodama modeliranja:

Prilikom postavljanja analitičkog matematičkog modela reaktora suočeni smo s rješavanjem niza diferencijalnih jednadžbi koje zahtijevaju primjenu numeričkih metoda i programiranja. Taj se problem također pojednostavljuje primjenom neuronskih mreža.

3. Jednostavna, brza, pouzdana i prilagodljiva primjena.
4. Pristupačna cijena.

## Modeliranje pomoću neuronske mreže

Neuronske mreže (ANN, artificial neural networks) su matematički opis biološkog neuronskog sustava. Može se reći da oponašaju ljudski proces učenja. Osnovnu

jedinicu čini neuron koji slično neuronima u ljudskom tijelu obavlja nelinearne matematičke modifikacije. Neuroni složeni u jedan ili više slojeva čine strukturu mreže.

Postupak primjene neuronske mreže započinje odabirom nezavisnih i zavisnih veličina, te strukture mreže. Postupak modeliranja se provodi u 3 koraka:

1. Treniranje neuronske mreže: provodi se tako da se eksperimentalni podaci koriste za treniranje modela, tj. određivanje parametara modela s ciljem postizanja minimizacije odstupanja između procijenjenih i eksperimentalnih podataka.
2. Testiranje neuronske mreže: neuronska mreža s određenim parametrima testira se na novom skupu eksperimentalnih podataka.
3. Identifikacija.

Iako je modeliranje neuronskom mrežom najčešće jednostavnije od modeliranja analitičkim metodama, znanje o procesu jedna je od ključnih značajki za uspješno izvođenje modela. Dobro poznavanje procesa važno je zbog definiranja nezavisnih i zavisnih veličina sustava kao i za procjenu i interpretaciju dobivenih rezultata modela.

Za uspješno stvaranje modela pomoću neuronske mreže ključni su procesni podaci. O njihovom broju i kvaliteti ovisi koliko će postavljeni model dobro opisivati realno stanje. Osim procesnog znanja i procesnih podataka, za stvaranje matematičkog modela pomoću neuronske mreže potreban je određeni alat, tj. programski sustav. Navedene tri osnovne značajke potrebne za modeliranje neuronskom mrežom prikazane su slikom 1.

Slika 1: Osnovne značajke za modeliranje pomoću neuronske mreže



## Primjena softverskog analizatora u praksi

Proces hidrodesulfurizacije jedan je od ključnih procesa u preradi nafte. Važnost procesa je još naglašeniji posljednjih godina stalnim postroženjem zahtjeva kvalitete proizvoda i tendencijom smanjenja sadržaja sumpora u motornim gorivima. Kako se



sirovine prije uvođenja u reaktor. Postrojenje se sastoji od 2 reaktora, od kojih prvi ima 2 sloja katalizatora. Postrojenje je namijenjeno za izmjenični rad kao postrojenje hidrodesulfurizacije i kao postrojenje blagog hidrokrekinga. Od 3 sloja katalizatora, prvi je po svojim svojstvima namijenjen reakcijama hidrodesulfurizacije, dok su druga 2 sloja po svojstvima prilagođena reakcijama blagog hidrokrekinga.

U prvom sloju katalizatora uvođenjem sirovine u atmosferi bogatoj vodikom odvijaju se reakcije desulfurizacije, denitrifikacije, hidrogenacije i deciklizacije. Najzastupljenije su reakcije desulfurizacije, prilikom čega se troši vodik i razvija toplina. Razvijanjem topline dolazi do povišenja temperature kroz katalitički sloj, a povišenje temperature se mjeri pomoću indikatora temperature.

U druga dva sloja katalizatora uvodi se smjesa plina za hlađenje, a količina plina se regulira regulacijom protoka.

Produkti reaktora se zatim provode kroz sekciju predgrijavanja sirovine i nakon hlađenja uvode u visokotlačni separator u kojem se u vrhu izdvaja plin bogat vodikom, dok se kapljevita smjesa ugljikovodika uvodi u niskotlačni separator. Ukapljeni ugljikovodici s dna niskotlačnog separatora se nakon hlađenja uvode u kolonu za stripiranje, dok se plin s vrha NT separatora provodi u sekciju obrade plina aminom. Nakon odvajanja kapljevite smjese ugljikovodika kroz kolonu, kao proizvod vrha kolone izdvaja se nestabilizirani benzin, dok se u dnu kolone izdvaja odsumporeno plinsko ulje. Gustoća i udio sumpora plinskog ulja određuje se laboratorijski nekoliko puta dnevno.

### **Softverski analizator sumpora u lakom plinskom ulju**

Eksperimentalni podaci procesa prikupljeni su svakodnevno u razdoblju od 5.10.2005. do 2.4.2006. Količina podataka ograničena je na jednu analizu dnevno. Procesna mjerenja provode se kontinuirano, a prikupljaju se i bilježe pomoću procesnog računala i programskog sustava Process Historian Data.

Analiza procesa je ograničena na proučavanje statičkih karakteristika procesa, pa je provedena selekcija podataka kako bi se dinamički utjecaj minimizirao. Selekcija podataka je provedena tako da su analizom obuhvaćeni samo podaci za koje se iz procesnih mjerenja utvrdilo da su rezultat stabilnog rada procesa. Sažeti prikaz eksperimentalnih podataka prikazan je tablicom 1.

Ukupan broj uzoraka je nakon navedenih ograničenja sveden na 90.

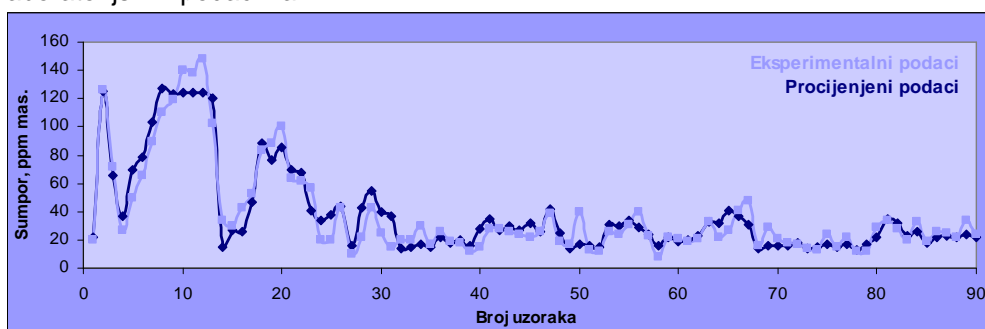
U izradi softverskog analizatora s primijenjenom neuronskom mrežom provedeni su sljedeći postupci:

1. Analiza eksperimentalnih podataka.
2. Definicija nezavisnih i zavisnih veličina.
3. Treniranje neuronske mreže.
4. Testiranje neuronske mreže.
5. Identifikacija neuronske mreže.
6. Primjena softverskog analizatora na postrojenju hidrodesulfurizacije.

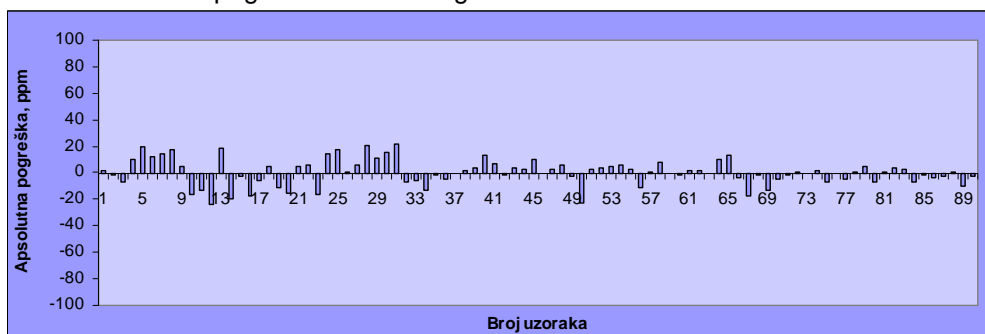
Tablica 1: Prikaz eksperimentalnih veličina

Veličina	Mjerna jedinica	Metoda mjerenja
Ukupan protok sirovine	kg/h	Proces
Gustoća sirovine	kg/dm <sup>3</sup>	Lab
Udio sumpora u sirovini	% mas	Lab
Ulazna temperatura u 1. sloj katalizatora	°C	Proces
Tlak na ulazu u 1. sloj katalizatora	bar	Proces
Razlika temperatura kroz 1. sloj katalizatora	°C	proces
Razlika temperatura kroz 2. sloj katalizatora	°C	Proces
Razlika temperatura kroz 3. sloj katalizatora	°C	Proces
Protok svježeg vodika u proces	kg/h	Proces
Gustoća desulfuriziranog plinskog ulja	kg/dm <sup>3</sup>	Lab
Udio sumpora u desulfuriziranom plinskom ulju	% mas	Lab

Slika 3: Usporedba procjene udjela sumpora softverskog analizatora s laboratorijskim podacima



Slika 4: Relativna pogreška softverskog analizatora



Rezultati matematičkog modela prikazani su slikom 3 na kojoj se vidi usporedba eksperimentalnih podataka sa procijenjenim podacima, rezultatom matematičkog modela.

Relativna pogreška modela u usporedbi s eksperimentalnim podacima prikazana je slikom 4.

Primjena softverskog analizatora trenutačno je u probnom radu na postrojenju hidrodesulfurizacije Rafinerije nafte Rijeka i u skoroj budućnosti analizator će biti primijenjen kao mjerna točka na zaslonu distribuiranog kontrolnog sustava.

## Zaključak

Prikazana je primjena matematičkog modeliranja u svrhu određivanja fizikalno-kemijskih svojstava i sastava proizvoda. Softverski analizator kojim se određuje udio sumpora u proizvodu hidrodesulfurizacije pokazao se primjenjiv kao nadopuna laboratorijskim analizama u nedostatku hardverskog procesnog analizatora.

Također je prikazano kako je primjena matematičkog modeliranja neizostavna prilikom unapređenja vođenja, mjerenja i optimizacije procesa, a najbolji rezultati postižu se kombinacijom matematičkih metoda umjetne inteligencije s analitičkim određivanjem i inženjerskim prosuđivanjem. Dobiveni rezultati pomiču granice u rješavanju problema vođenja, mjerenja i optimizacije procesa.

# SOFTWARE SENSORS IN IMPROVING PRODUCT QUALITY AND HDS PROCESS CONTROL

## *Abstract*

*Today, we are witnessing the necessity to produce high quality fuels in our refineries. To meet the market needs, refining processes must be equipped with a satisfactory number of process analyzers, which is not always easy, because of their price. In the past ten years, there has been a significant number of software sensors present in the process industry. Their application is based on process model built from process data in order to continuously, on-line, predict physical and chemical properties or product content and improve process monitoring and control.*

*In this paper, practical application of software sensor based on neural networks was explored on the actual case of sulfur content in the hydrodesulphurization unit product, LGO. The research results shall be applied in practice.*



## Introduction

Experimental data and measurements from industrial plants through the application of different process analysis methods may be used both for process monitoring and control, as well as for model development and determination of individual process parameters. Due to fuel quality requirements and the need for advanced process control, the need for accurate measurement of process units and physico-chemical properties is increasing daily. Recently, along with the inevitable hardware sensors, increasingly present in the process industry are the software sensors. Software sensors are based on a mathematical model enabling on-line evaluation of the physico-chemical properties and the chemical composition. They are applied both individually and as an addition to the classical hardware process analyzers.

Software sensors may be based on a mathematical analytical model applying physico-chemical laws, data mining, or artificial intelligence application methods i.e. neural networks. The application of analytical models is becoming limited with the complexity of the studied system. Due to the complexity of systems in process industry, the elaboration of analytical models – apart from know-how – requires also a large amount of experimental data, and often lengthy experimental research. That is why most frequently used for the application of software sensors are the mathematical models based on neural networks.

## Application of Software Sensors

Today, neural networks have a wide application worldwide: in investment analyses, forensic analyses, process control and monitoring, for discovering malfunctions and breakdowns in airplane, railroad, and other industries, and the like. One of the most frequent applications of neural networks in the process industry is for the purpose of making software sensors.

The application of software sensors based on neural network may be as follows:

1. Application as an addition to or replacement of hardware process analyzers and laboratory analyses:

During regular servicing of devices or their malfunction, the software sensor continues to perform property analysis based on the mathematical model and historical process data enabled by the so far work of the hardware sensor. Apart from that, hardware sensors provide analysis results each 10-15 minutes, whereas the software sensor is capable of presenting results each minute, if necessary. Through parallel operation, software sensor may often reveal an error produced by the hardware analyzer.

2. Application for individual determination of the physico-chemical properties or the chemical composition:

Software sensors may perform individual determination of the physical and chemical properties or the chemical composition, unless there is a hardware analyzer, while

the laboratory analyses are performed several times a day. One among frequent individual uses is also for determining gas emission, as well as detecting the source of noxious gases, thus replacing other costly devices.

### 3. Application in advanced process monitoring and control:

Given that all points of a distributed control system may be a part of the neural network mathematical model, process data may be used for advanced process control, detection of hot spots fault detection, determination of process bottlenecks; for process optimization, and the like.

### 4. Application for advanced process control

The main purpose of applying advanced process control is increased yield and product quality, which is impossible to achieve without a large number of process analyzers. Since the determination of numerous properties does not require hardware process analyzers, often costing more than the entire project in question, the properties may be determined using software sensors.

Examples of concrete application of software sensors based on neural network are as follows:

- determination of the product's physical and chemical properties, such as, for example, boiling point, flash point, pour point, vapour pressure, yields, chemical composition, octane number, etc.
- determining gas emission,
- mathematical modeling of distillation columns, determining the chemical composition of top and bottom, determining column yields,
- mathematical modeling of reactors,
- estimation of operation and pollution of heat exchanger walls, and the like,
- economic estimations.

The advantages of software sensors with the applied neural network are as follows:

### 5. They do not require a large number of parameters, or lengthy experimental research.

In order to set up an analytical model of e.g. a hydrodesulfurization process reactor, long-term experimental research is required, including also an analysis of the laboratory reactor. Also, a large number of parameters is needed, often impossible to determine experimentally, or find in the references. Setting up a mathematical model based on neural network constitutes a solution for the above mentioned problems, since it is based on the hystorical data of the reactor in question.

### 6. Possibilities of simplifying complex non-linear systems, impossible to solve by classic modeling methods.

While setting up an analytical mathematical reactor model, we are faced with the need to resolve a number of differential equations, requiring the application of numerical methods and programming. This particular issue is also simplified through the application of neural networks.

7. Simple, fast, reliable and flexible application,
8. cost effectiveness.

## Modeling Using Neural Network

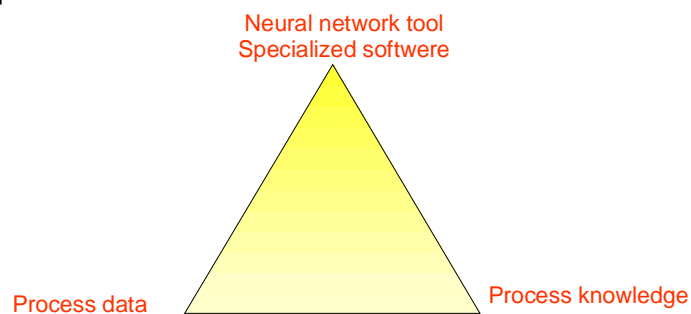
Neural networks (ANN, artificial neural networks) are mathematical descriptions of the biological neural system. One might say that they imitate the human learning process. The basic unit is the neuron, which – similarly to neurons in the human body - performs non-linear mathematical modifications. Neurons combined into one or more layers make the network structure.

The procedure of applying neural networks begins by a selection of dependent and independent variables, as well as the network structure. The modeling process is performed in 3 steps:

1. Neural network training: the experimental data are used for model training i.e. determination of model parameters in order to achieve minimal aberration between the estimated and the experimental data.
2. Neural network testing: neural network with specific parameters is tested on a new group of experimental data.
3. Identification

Although the modeling using neural network is mostly simpler than the modeling using analytical models, the knowledge of the process is one among the key prerogatives for successful modeling. Good mastery of the process is important for defining dependent and independent variables, as well as for estimating and interpreting the obtained model results.

Figure 1: Application of artificial neural networks

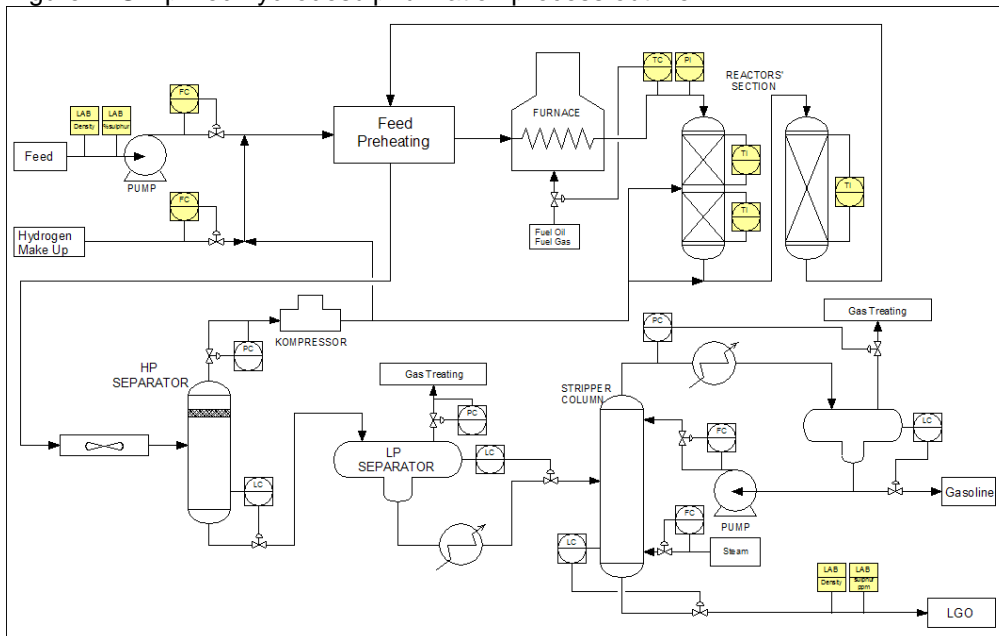


For a successful model creation using neural network, process data are of key importance. Their number and "quality" determine how well shall the set up model describe the real condition. Apart from the process-related knowledge and process data, the creation of a mathematical model using neural network requires certain tools i.e. software. The above three basic properties necessary for modeling using neural network are shown in Figure 1.

### Software Sensor Practical Application

Hydrodesulphurization process is among the crucial ones in oil procesing. The importance of the process has been even more stressed in the recent years, through constant rendering of product quality requirements more stringent and the tendency of reducing the motor fuels sulphur content. Since the process of desulphurization reduces the share of sulphur and other compounds in petroleum fractions, the sulphur share in the product, which is the gas oil, is the key value for process control and product quality monitoring.

Figure 2: Simplified hydrodesulphurization process outline



Due to motor fuel quality requirements in Croatia, for the application of the software sensor, we have chosen the hydrodesulphurization plant of the Rijeka Refinery. A software sensor has been elaborated for determining sulphur content in the product, light gas oil. A simplified outline of the process, with the most important measurements and key regulation circles, is shown in Figure 2.

## Hydrodesulphurization Process Description

The feed: gas oil, is introduced into the plant, mixed with a blend of fresh and recirculating hydrogen-rich gas, and conducted through the pre-heating section, where it is heated by exchanging heat with reactor products, through a series of heat exchangers. Total plant capacity is regulated through flow regulation, while feed properties, density, and sulphur compounds share, are determined in the laboratory several times a day. The pre-heated feed passes through the furnace and is introduced into the first catalyst layer. Input feed temperature is regulated through the effect of temperature regulation on the flow of energents into the furnace, while feed pressure before its introduction into the reactor is also measured. The plant consists of 2 reactors, the first one having 2 catalyst layers. The plant was intended for an alternating operation, as hydrodesulphurization/mild hydrocracking plant. Out of 3 catalyst layers, the first one is, by its properties, intended for reactions of hydrodesulphurization, while the properties of the remaining 2 layers have been adjusted to mild hydrocracking reactions.

In the first catalyst layer, by introducing the feed into an atmosphere rich in hydrogen, desulphurization, denitrification, hydrogenation and decyclization reactions are taking place. Most frequent are the desulphurization reactions, consuming hydrogen and generating heat. Heat generation causes temperature increase through the catalytic layer, with temperature increase being measured by indicators.

A cooling gas blend is introduced into the remaining two catalyst layers, with gas volume being regulated through flow regulation.

The reactor products are then conducted through the section of feed pre-heating. After cooling, they are introduced into a high pressure separator in whose top the hydrogen-rich gas is isolated, while the fluid hydrocarbon blend is introduced into the low pressure separator. Liquid hydrocarbons from the bottom of the low pressure separator are, after cooling, introduced into the stripping column, while the gas from the top of the low-pressure separator is conducted into the section of gas treatment using amine. After the separation of the liquid hydrocarbon blend through the column, as a top column product, unstabilized gasoline is isolated, while, on the bottom of the column, desulphurized gas oil is isolated. Density and sulphur share of the gas oil are determined at a laboratory several times a day.

### Sulphur Software Sensor in Light Gas Oil

The experimental data of the process have been collected daily in the period from 5 Oct, 2005 to 2 Apr, 2006. Data volume has been limited to one analysis per day. Process measurements are performed on-line, collected and noted by the process computer and the Process Historian Data software.

Process analysis has been limited to the study of static process properties, so that a data selection has been performed, in order to minimize the dynamic impact. Data

selection has been performed by including into the analysis only the data established through the process measurements as the result of stable process operation. A summarized review of the experimental data is provided in Table 1.

The total number of samples was – after the above mentioned limitations – brought down to 90.

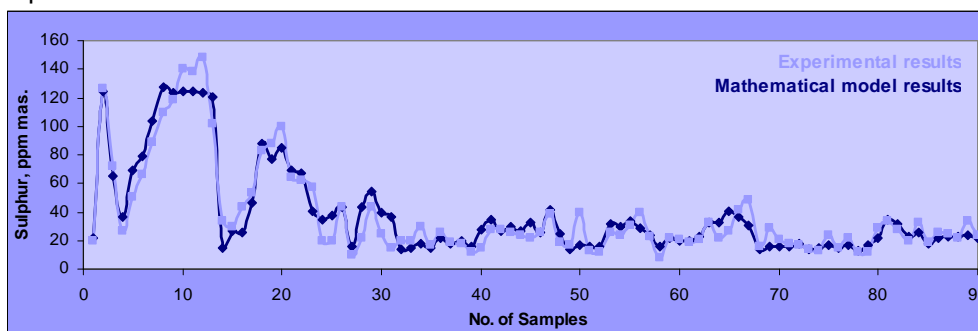
Table 1: Experimental variables

Value	Unit of measure	Measurement method
Total feed flow	kg/h	Process
Feed density	kg/dm <sup>3</sup>	Lab
Feed sulphur share	%mas	Lab
Input temperature in the 1 <sup>st</sup> catalyst layer	°C	Process
Input pressure in the 1st catalyst layer	bar	Process
Temperatural difference in the 1st catalyst layer	°C	process
Temperatural difference in the 2nd catalyst layer	°C	Process
Temperatural difference in the 3rd catalyst layer	°C	Process
Hydrogen make up process flow	kg/h	Process
Density of desulphurized gas oil	kg/dm <sup>3</sup>	Lab
Sulphur share in desulphurized gas oil	% mas	Lab

In the elaboration of a software sensor with the applied neural network, the following procedures have been performed:

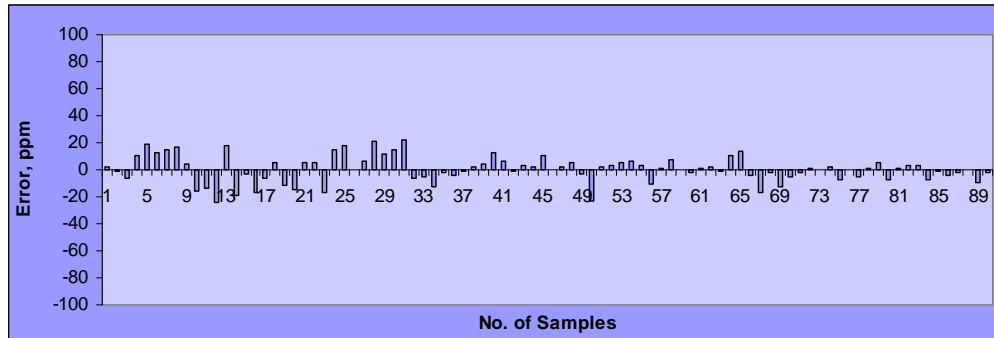
1. Analysis of experimental data
2. Defining of dependent and independent values
3. Training of the neural network
4. Testing of the neural network
5. Identification of the neural network
6. Application of the software sensor at the hydrodesulphurization plant.

Figure 3: Comparison of sulphur value obtained by software sensor with experimental data



The results of mathematical model are shown in Figure 3, showing a comparison of experimental data with the estimated data, resulting from the mathematical model. Relative model error compared with experimental data is shown in Figure 4.

Figure 4: Relative error of software sensor



The software sensor application is currently being tested at the Rijeka Refinery hydrodesulphurization plant. In the near future, the sensor shall be applied as a point of measure on the screen of the distributed control system.

## Conclusion

The paper presents the application of mathematical modeling in the determination of physical and chemical properties and composition of the product. The software sensor determining sulphur share in the product of hydrodesulphurization has proven as applicable in the sense of addition to laboratory analyses, in the absence of a hardware process analyzer.

The paper shows that the application of mathematical modeling is essential for advancing process control, measurement and optimization, while the best results are achieved through a combination of artificial intelligence mathematical methods with analytical determination and engineer reflection. The obtained results shift the boundaries in resolving the issue of process control, measurement and optimization.

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UDK	ključne riječi	key words
665.658.62	HDS katalitička desulfurizacija	HDS catalytic desulfurization
66- 933.6	automatizirani, kompjuterski vođeni proces	automated, computer controlled process
681.542.2	sustav za vođenje kemijskog sastava	chemical composition control system
681.513.7/.8	neuronska mreža	neural network
681.513.7	samoučeći sustav vođenja	selflearning control system
681.513.8	samoorganizirajući sustav vođenja	selforganizing control system

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