Quality Soft Sensor Design for Crude Oil Desalting/Dehydration Unit Using Local Instrumental Variable (LIV) Approach

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Abstract
Oil produced in most oil fields is accompanied by water which normally contains soluble salts such as chlorides of sodium, calcium, and magnesium that must be treated. If crude oil is left untreated, when it is processed in a refinery the salt can cause various operating problems. Desalting/dehydration plants (DDP) are often installed in crude oil production units in order to remove water-soluble salts from an oil stream. The product quality is only obtained through laboratory analysis with significant delays that makes it difficult to maintain continuous monitoring and accurate control of the unit. This paper describes the development of data-driven soft sensor for product quality of the oil desalting/dehydration process. The product quality is determined using salt removal efficiency, which is expected to be affected by five secondary variables as heating, settling time, chemical dosage, mixing time and wash water. The soft sensors are constructed based on novel state-dependent parameter (SDP) modelling method by local instrumental variable (LIV). The results showed that proposed soft sensor can be applied for DDP quality estimation as an alternative to laboratory testing. So, it becomes possible to continuously estimate product quality and to reach robust plant control system.

Keywords: Data-driven soft sensor, Crude oil desalting/dehydration unit, Quality prediction, State dependent parameter (SDP), Local instrumental variable (LIV) approach

Introduction
Continuous monitoring and control of product quality in process industry is a challenging issue. This is because, for most processes a proper hardware sensor is not available for continuous measurement. Even when such sensors are available, they have low reliability and require frequent calibration or add significant delays. Therefore, the use of inferential models known as soft sensors for continuous process monitoring has gained much popularity in the last decade. Soft sensors have been used to model the relationship between secondary variables (or easy-to-measure variables) such as temperature, pressure and flow and primary variables (or difficult-to-measure variables) such as quality variables, quantify the productivity or the specifications upon which the product is sold (e.g., purity, physical or chemical properties) [1].
The soft sensor models are mostly developed from input-output process data because of the availability of such data in the industrial plant history. The data-driven soft sensors are

developed using statistical and soft computing based techniques such as multiple linear regression (MLR), partial least squares (PLS), principal component analysis (PCA), artificial neural networks (ANN), neuro-fuzzy system (NFS), support vector regression (SVR) and modified approaches [2]. The state-dependent parameter (SDP) modelling approach is an identification and modelling technique, which was introduced by Peter C. Young and co-workers [3] and its application for soft sensor development has been carry out in recent years [4-6]. Bidar et al. [7] proposed the novel SDP method by using local instrumental variable (LIV). The LIV approach has been used polynomial modelling combined with instrumental variable (IV) concepts to introduce the simultaneous estimation method of state-dependent parameters. Furthermore, application of LIV approach has proven successful in developing LIV-based soft sensors in an atmospheric distillation unit.

Oil desalting/dehydration systems are industrial processes for removing water-soluble salts from an oil stream. The primary objective for an oil desalting/dehydration process is to achieve sufficient product purity in terms of salt removal and water cut efficiencies. Producing oil with good product quality is an important issue, therefore, constructing soft sensors for modeling an oil desalting/dehydration system is essential. Although, a number of study [8-12] cover modeling, optimization and estimation techniques in DDP systems, there is a lack of research on the application of soft sensors in desalting/dehydration process.

In this paper, a new data-driven soft sensor has been proposed to predict the salt removal efficiency with five secondary variables as heating, settling time, chemical dosage, mixing time and wash water. The LIV approach are employed to develop soft sensor and satisfactory results are obtained in compared with real observation data.

Case study: Desalting/Dehydration unit

Fig. 1 shows the schematic of specific a crude oil DDP unit. Dissolved salts and water were removed from oil flow in six major steps: separation by gravity settling, chemical injection, heating, addition of fresh (less salty) water, mixing, and electrical coalescing. Finally, the amount salt in crude oil must be reduced to 5 PTB (pound of salt per thousand barrels of oil). In this plant, two-stage desalter is used to remove more amounts of water from oil flow. Detailed information about the unit have been discussed in [13]. The specifications of crude oil, which is concerned to a Kuwaiti oil well are shown in Table 1. In carrying out the experiments, samples were first tested for salt in PTB, in which the details of these tests, are presented elsewhere [14, 15].

Methodology

In a desalting/dehydration process, there are several parameters that can be considered to reach an optimum combination of operating conditions. In the present study, five parameters are selected to identify soft sensing models for salt removal efficiency, which are listed in Table 2. The input-output dataset for DDP unit had been collected by conducting 980 experiments in order to study the effects of these five parameters on the unit [15]. The dataset is divided into two parts by randomization: the training dataset (consisted of 90% of the total data) and the testing dataset for evaluating the performance of proposed soft sensor. The salt removel efficiency is prepared by experimental data [13] and is calculated from Eq. (1).

$$\eta = 1 - \frac{Z_{out}}{Z_{in}} \tag{1}$$

where Z_{out} denotes outlet salt result (PTB) and Z_{in} denotes inlet salt result (PTB).

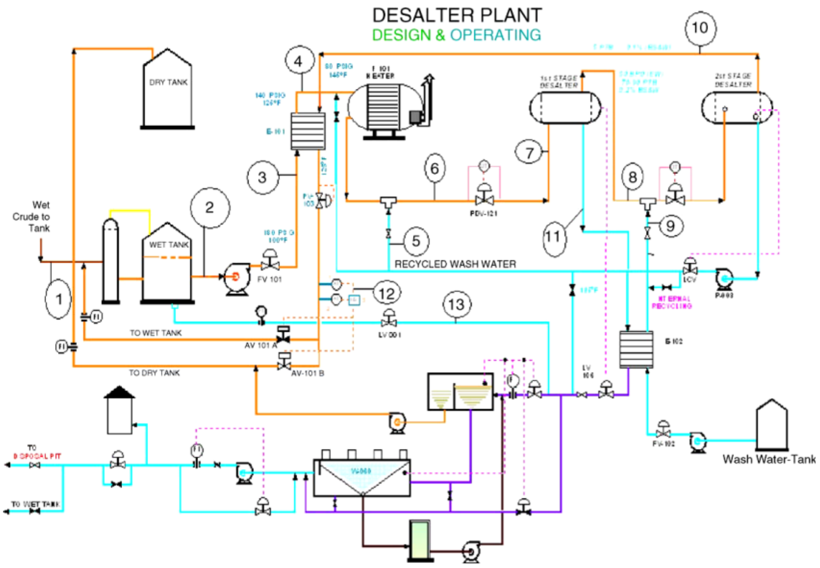

Fig. 1. Schematic of crude oil desalting/dehydration plant [12]

Table 1. Characteristics of crude oil samples [12]

Property	Value
Specific gravity	0.864
Reid vapour pressure (Psia)	10.5
Pour point (ºF)	Less than −30.0
Average API gravity at 60 ºF	31.7
Viscosity (Cs) at 70 ºF	17.4
Viscosity (Cs) at 100 ºF	10.5
Viscosity (Cs) at 130 ºF	6.79
Viscosity (Cs) at 160 ºF	4.8
Average Sulphur content (wt.%)	2.7
Asphaltenes (wt.%)	2.23

Table 2. Detailed description of secondary and primary variables of DDP unit [12]

Parameter	Variable	Values
Temperature (ºC)	X_1	55 ºC (low), 70 ºC (high)
Settling time (min)	X_2	1 min (low), 3 min (high)
Mixing time (min)	X_3	1, 3, 5, 7 and 9
Demulsifier dosage (ppm)	X_4	1, 2, 5, 8, 10, 12 and 15
Dilution water (%)	X_5	1, 2, 3, 4, 6, 8 and 10
Salt removal efficiency, η	y	

The identification of soft sensing model between secondary and primary variables is performed based on SDP modeling in the following form:

$$\begin{cases} y_t = \sum_{i=1}^{n} a_{i,t} \cdot z_{i,t} + e_t \\ a_{i,t} = a_i\left(x_{1,i,t}, x_{2,i,t}, \ldots, x_{ns_i,i,t}\right) \end{cases} \quad , \quad \forall t \ , \ e_t = N\left(0, \sigma^2\right) \tag{2}$$

Here y_t is the model output, n is the number of SDPs/regressors, $z_{i,t}$ is the i^{th} regressor and $a_i(\cdot)$ is the i^{th} SDP that is a function of ns_i correspondent states ($x_{j,i,t}$, $j = 1,2,\ldots,ns_i$). In the case, where $a_{i,t}$ is not state dependent, $ns_i = 0$. e_t is a zero mean white Gaussian distributed unknown noise with variance σ^2. In local polynomial modeling which combined with IV

concepts, the functionality of each SDP is defined by a local polynomial in the state variable space. The parameters of these polynomials are locally estimated by using IV method. For more information about SDP/LIV approach can refer to [5-7].
To evaluate the performance of the soft sensing models, three numerical indicators are used: the root mean square error (RMSE), mean absolute error (MAE) the coefficient of determination (R^2) and adjusted R^2, which are calculated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\left(y_i - \hat{y}_i\right)^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\hat{y}_i - \overline{y})^2}{\sum_{i=1}^{N}(y_i - \overline{y})^2} \tag{4}$$

$$R^2_{adj} = 1 - \left[\frac{\left(1-R^2\right)\left(N-1\right)}{(N-k-1)}\right] \tag{5}$$

where, N is the number of data samples, k is the number of independent regressors or predictors and y_i , $\hat{y}_i$, $\overline{y}$ and $\overline{\hat{y}}$ are referred to as the real value, predicted value, mean values of y and $\hat{y}$, respectively.

Results and discussion

The SDP-LIV model structure for salt removal efficiency according to Eq. (1) is expressed in following form:

$$y_t = a_{1,t}\left\{X_1, X_2, X_3, X_4, X_5\right\} \times 1 + e_t \tag{6}$$

where y_t represents the predicted value of y for the t^{th} query sample. All secondary variables are considered as states of a_t and correspondent regressor is chosen as one. The local polynomial with the zero order is selected for each state variable. The LIV parameters are optimized and then soft sensor model can be trained with the optimum parameters. The training procedure is repeated until model configuration with the best performance has been achieved. The results indicate that all five secondary variables are the influential variables in estimating salt removal efficiency. The model performance indicators for training and testing dataset are provided in Table 3.

Table 3. Performance indexes of proposed soft sensor on training dataset

Training performance indexes			**Testing performance indexes**		
R^2	R^2_{adj}	RMSE	R^2	R^2_{adj}	RMSE
1	0.9999	0.6663	1	0.9999	1.4589

The RMSE show that the soft sensor model have high accuracy, while R^2 value is very close to 1, which represents a good prediction performance. Furthermore, the similarity of R^2 value to adjusted R^2 means those irrelevant variables have not been considered into the soft sensing model. A comparison of the real observation data obtained by laboratory analysis and the soft sensor for testing dataset, is shown in Fig. 2. As can be seen, the outputs of LIV-based soft sensor match the real values of salt removal efficiency and follow the varying trend very well. Fig. 3 shows the real and predicted values of salt removal efficiency. Most of the data points fall close to the 45 degree line with slight deviations in some points which indicates good prediction performance of the model.

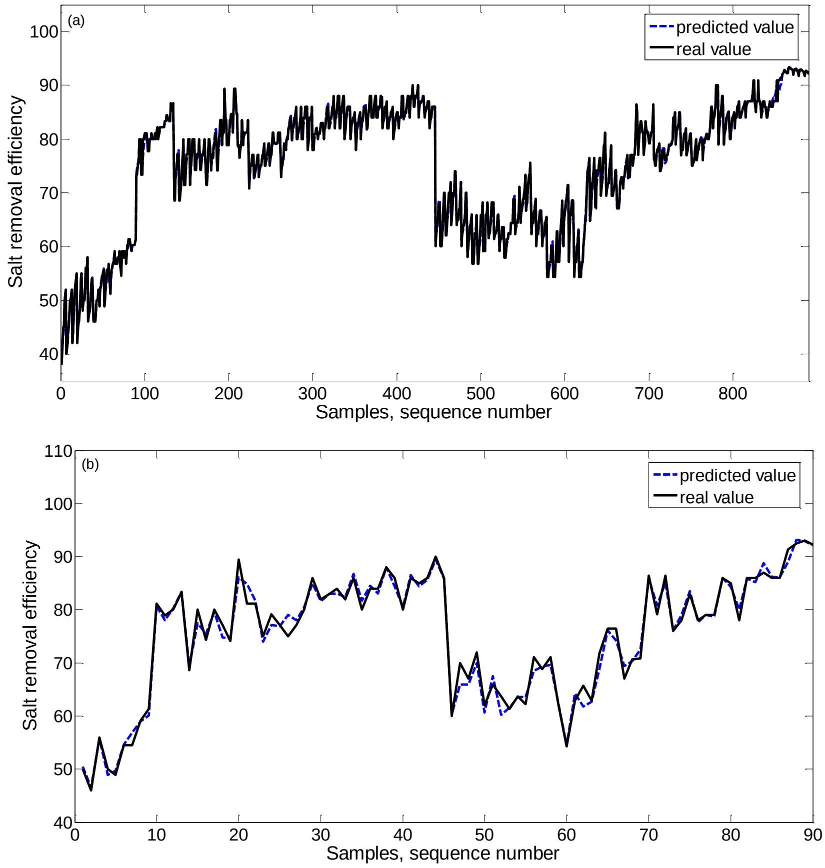

Fig. 2. Prediction results of salt removal efficiency on (a) training dataset, (b) testing data set

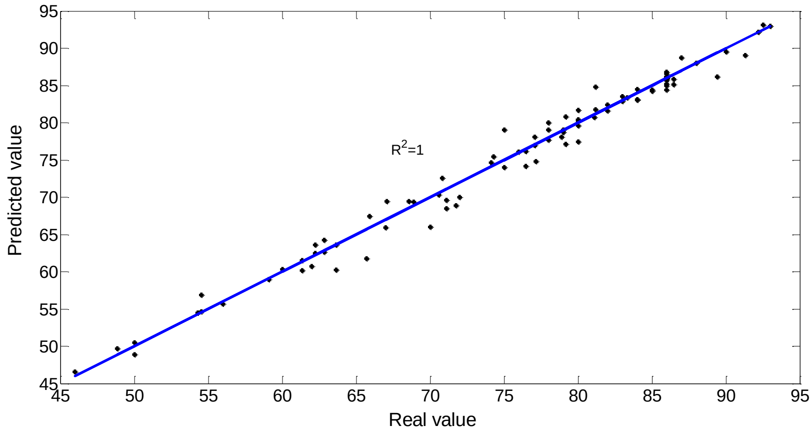

Fig. 3. Predicted and real value of salt removal efficiency

Conclusions

In this paper, local instrumental variable (LIV) approach are employed for estimating salt removal efficiency of a real operating oil desalting/dehydration plant. The soft sensor model shows results with deviations within an acceptable range, and performance indicators suggest that the proposed model can be used in monitoring and control system of desalting/dehydration plant. Furthermore, the excellent performance indicates that the LIV-based soft sensor provides a powerful tool for soft sensor modeling.

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