

Review

Petroleum Classification Methods and Their Application to Crude Oil Selection for Refinery Operations: A Critical Review

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Abstract

Various petroleum classifications have been developed over the years using different crude oil characteristics, techniques, and approaches. A review of all these classifications made so far has not been published in recent decades and no relation to the crude oil selection process has been investigated yet. Crude oil selection is a very delicate process, requiring the right balance between crude oil purchase costs, which can account for up to 95% of total refining costs, and minimizing the risk of unplanned shutdowns, which can result from undesirable asphaltene precipitation, equipment fouling, accelerated corrosion, and disruptions in the operation of desalters and other process units. The current research conducts a review of the distinct petroleum classifications published in the literature and discusses their possible link to the expected performance of a modern high complexity petroleum refinery in terms of minimizing the risk of unplanned shutdowns. An intercriteria analysis approach is proposed as a tool to discriminate those crude oils from a database of comprehensive assays of 1390 crude oils, which may invoke a possible unplanned shutdown of the petroleum refinery under study based on a previous experience.

Keywords: petroleum; refining; classification; characterization; intercriteria analysis



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1. Introduction

Petroleum is a pillar of economic and national security, as gross domestic product (GDP) is highly proportional to the daily quantity of refined crude oil (Pearson correlation coefficient $R = 0.94$) [1]. It provided about 30% of the world's energy production in 2025, followed by coal (about 27%), natural gas (23%), renewables (15%), and nuclear power (5%) [2]. In 2025 the demand for crude oil reached the all-time high of 105.15 mb/d (million barrels per day) [3]. In addition to the energy it supplies, crude oil is a feedstock for production of the fundamental chemical building blocks, known as petrochemicals, on which innumerable base materials are produced [4]. It is an extremely complex mixture containing hydrocarbon components having between two and over 120 carbon atoms in their molecules. The number of potential organic compounds having such a broad carbon

number range has been estimated at 10^{60} [5]. In addition to hydrocarbons, petroleum also contains organic compounds containing heteroatoms (nitrogen, sulfur, oxygen, and metals), that vary in composition, structure, and molecular weight [6–9]. Alkane hydrocarbons in petroleum were found to range from traces of C_2H_6 , dissolved in the liquid petroleum, to $C_{78}H_{158}$ [10]. Cycloalkanes were reported to have between one and 11 cyclic rings, with a maximum carbon number of 92 [11]. Arenes were reported to have between one and 18 condensed rings [12] (see Figure 1). Heteroatomic compounds in petroleum contain between one and several heteroatoms per molecule, categorized into groups such as O_x (classes O_1 , O_2 , O_3 , O_4 , and O_5), N_1O_y (N_1O_1 , N_1O_2 , N_1O_3 , N_1O_4 , and N_1O_5), O_xS_1 species (O_1S_1 , O_2S_1 , O_3S_1 , O_4S_1 , and O_5S_1) and O_xS_2 , (O_1S_2 , O_2S_2 , O_3S_2) [13]. The distribution of the diverse organic substances in different crude oils varies significantly, rendering each oil composition unique. This enormous variety of compositions makes the field of petroleum chemistry and technology an inherently complex and challenging endeavor.

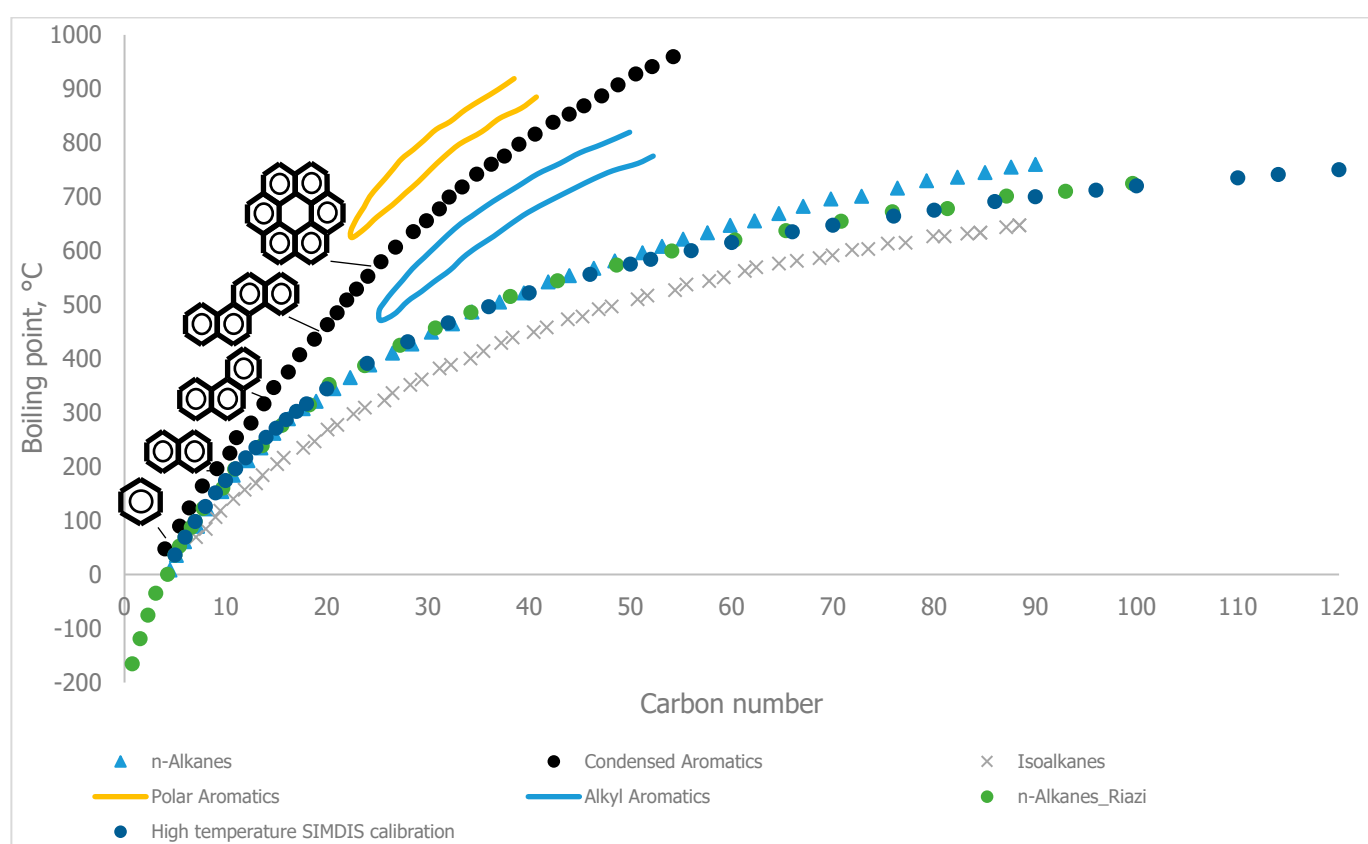


Figure 1. Relationship between the number of carbon atoms and the boiling point of the various hydrocarbons and their polar derivatives found in crude oil [7].

The number of traded crude oils is reported to be over 150 [14,15], although thousands have been characterized [16]. Over the years, several classifications have emerged that divide different oils into various classes based on criteria such as those mentioned in Section 2.1 (“Methods to Classify Crude Oils”) [17–26]. Depending on the extraction method used for the crude oil from the earth, petroleum oils are classified as conventional and unconventional. Conventional oils are extracted from the earth by pumping operations as free-flowing dark- to light-colored liquids [27]. They have a specific gravity ranging from about 0.810 to 0.985 and represent 30% of all oil reserves [27–29]. Unconventional crude oils refer to oils, which are not accessible through traditional drilling methods and are characterized by low-permeability rocks [30–32]. These oils are those that are either not fluid enough at reservoir conditions to be pumpable, or not fluid enough after production

at ambient surface conditions to be pumpable; in some cases, they exhibit both issues. Consequently, unconventional oils are divided into tight oil, heavy and extra heavy oils, and oil sands [33–35]. Tight oil reservoirs are characterized by very low porosity and permeability and often with small reservoir size, which require high-cost techniques such as hydraulic fracturing and horizontal drilling to recover the oil [36–38]. Tight oils are typically light crude oils having density at 15.6 °C lower than 0.8251 g/cm³ [39], but can exhibit specific gravity in the range between 0.7796 and 0.933 [38]. They are characterized by low levels of sulfur and nitrogen, occasional H₂S presence (which can be a problem), high alkane content, low levels of heavy metals (Ni and V) and sometimes high levels of alkaline metals, and other contaminants such as Ba and Pb may also be present [38]. Heavy and extra heavy oils have high viscosity, which prevents their extraction using conventional methods. Heavy oils are defined as having density at 15.6 °C between 0.920 and 1.000 g/cm³, and viscosity between 10 and 10⁴ cP [40–43]. They represent 15% of global oil reserves [24,28]. Extra heavy oils are those oils whose density at 15.6 °C is higher than 1.000 g/cm³ and their viscosity is higher than 10⁴ cP [41,44,45]. Their share of oil reserves is equal to 25% [24,28]. Oil sands consist of a blend of sand and bitumen that is highly viscous and solid at ambient conditions not enabling recovery using the conventional methods [46,47]. They represent 30% of global oil reserves [24,28].

Other classifications of crude oils are a function of their hydrocarbon composition, reflecting differing perspectives between geochemists and oil refiners [25]. The former group focuses on establishing the relationship between source rock chemistry and its maturity level by identifying and characterizing the crude oils [25,48–50]. In contrast, the latter group is more interested in the properties of crude oils, that may affect the operation and performance of refinery process units [51–55]. As can be seen from the data in Table 1, which shows the distribution of different hydrocarbons in all types of petroleum oils, the compositional variations are significant.

Table 1. Range of variation of the three hydrocarbon classes and the solubility class of asphaltenes in crude oils worldwide [24].

Hydrocarbon Type	Minimum Content, wt. %	Maximum Content, wt. %	Average Content, wt. %
Alkanes	15	60	30
Cycloalkanes	30	60	49
Arenes	3	30	15
Asphaltenes	5	50	6

Petroleum scientists established that physical properties—density (specific gravity), refractive index, viscosity and molecular weight—are related to the chemistry of petroleum [56–60], which may explain their use in the different classifications of petroleum [21,61]. Density or specific gravity is a fundamental property which correlates with the contents of saturates and aromatic structures (aromatic, resin, and asphaltene fractions) in the whole crude oil and its fractions [60]. This can explain why this property is used to classify the crude oils into extra light or condensates (*API* (American Petroleum Institute) gravity < 45°; specific gravity < 0.8017), light (*API* gravity = 34–45°; specific gravity = 0.8017–0.855), medium (*API* gravity = 22–33°; specific gravity = 0.8600–0.9220), heavy (10° < *API* gravity < 22°; specific gravity < 0.9220 < 1.000), and extra heavy (*API* gravity < 10°; specific gravity < 1.000) classes [61]. Another important property that affects not only quality but also the price of crude oil is its sulfur content [62–64]. Based on their sulfur content, crude oils are classified in low sulfur (S < 0.5%); medium sulfur (1.5% < S < 0.5%); high sulfur (3.1% < S < 1.5%); and extra high sulfur (S < 3.1%) [65].

Geochemists have found that the formation of oil is related to kerogen embedded in sedimentary rocks, which represents the residual organic matter from different stages of maturation [25,66,67]. Based on the H/C and O/C ratios four types of kerogen are categorized, type I (algal, aliphatic, H/C > 1.5; O/C < 0.1), type II (marine plankton, H/C of 1.0 to 1.4; O/C between 0.05 and 0.15), type III (terrestrial plants, H/C of 1.6 to 1.9, O/C between 0.1 and 0.3), and type IV (inert, non-generative, H/C $\leq$ 0.6, O/C > 0.1) [68]. The geochemical classification based on the three different kerogen types that can generate oil [67] can be used to classify crude oils in these three categories [69,70]. Another factor complementing crude oil classification is maturity, as increased maturation causes properties of oils derived from kerogen I and kerogen II to converge [69]. Therefore, kerogen type and maturity of crude oils provide quantitative criteria for crude oil selection in petroleum refineries [69].

Crude oils produced worldwide vary significantly from each other and are often mixtures of multiple sources, serving as feedstock in oil refineries [71–73]. Petroleum refineries are designed and constructed to accommodate the specific characteristics of the crude oil or blend of crude oils intended for processing [19]. Over time, due to changes in crude oil availability, used as the basis for the design of the refinery, shifts in oil markets, as well as geopolitical, economic and other factors, refineries are very often forced to select from available crude oils the appropriate blend for processing [74,75]. During feedstock selection, refineries must maintain facility integrity by minimizing the risk of unexpectedly high corrosion and high levels of fouling, complying with strict environmental regulations, and manufacturing products that meet global quality standards [7,76,77]. Crude oil classification is therefore critical in this process; for example, a refinery that is not designed to process crude oil classified as heavy and sour should not select crude oils within this classification group for processing [78]. However, given the numerous crude oil classifications—which will be discussed further in this research—one must determine which is most suitable for feedstock selection while meeting the requirements mentioned above. In 1988, Singh [79] reviewed and compared various classifications of crude oils based on physicochemical parameters across 27 different types of crude oils, presenting a classification of petroleum from the refiner perspective. He discussed methods for determining structural parameters of crude oils using nuclear magnetic resonance (NMR) spectroscopy and their characterization/classification via other instrumental techniques. The limitations of the methods and the broader significance of crude oil classification were highlighted [79]. To the best of our knowledge, no review since then has addressed petroleum classification and its relation to crude oil selection from a refiner's perspective. This gap motivated the current research.

This study aims to review the various classifications of crude oil published in the literature regarding their significance for the correct selection of crude oils and to identify the most useful ones that can ensure safe and cost-effective refinery operation using an intercriteria analysis approach.

2. Materials and Methods

2.1. Materials

This research analyzes data from comprehensive assays of 1390 crude oil samples, the property ranges of which are summarized in Table 2. These crude oils have been characterized and processed globally in petroleum refineries over the past 50 years.

Table 2. Range of variation of properties of studied crude oils.

	Minimum	Maximum
Specific gravity at 15.6 °C (API gravity)	0.7565 (55.6°)	1.016 (7.8°)
Refractive index at 20 °C	1.4244	1.5741
Kinematic viscosity at 40 °C, mm ² /s	0.502	48,300
Pour point, °C	−54	51.7
Sulfur, wt. %	0.0002	9.0
Nitrogen, wt. %	0.00	0.877
Nickel, wt. ppm	0.00	151
Vanadium, wt. ppm	0.00	1200
Total acid number (TAN), mg KOH/100 g	0.00	9.4
Molecular weight, g/mol	118	770
Watson characterization factor (K_W)	10.92	13.04
True boiling point (TBP) fraction yields, wt. %		
Gas	0.0	11.1
Light naphtha (C ₅ –100 °C)	0.0	33.6
Heavy naphtha (100–180 °C)	0.0	51.2
Kerosene (180–240 °C)	0.0	29.9
Diesel (240–360 °C)	4.6	52.0
Vacuum gas oil (360–540 °C)	0.8	62.5
Vacuum residue (>540 °C)	0.0	61.1
SARA (Saturates, Aromatics, Resins, Asphaltenes) composition		
Saturates, wt. %	18.5	97.6
Aromatics, wt. %	13.7	52.9
Resins, wt. %	0	19.9
C ₅ -asphaltenes, wt. %	0	30.1
C ₇ -asphaltenes, wt. %	0	20.5

The analytical scheme for the comprehensive assays performed on the 1390 studied crude oils is presented in Figure 2.

Figure 3 depicts the visual appearance of crude oils under study.

2.2. Methods to Classify Crude Oils

2.2.1. K_W -Characterization Factor and Other Characteristics of Petroleum Oils Related to K_W

Watson characterization factor is one of the empirical indices established to classify the crude oils [80–82]. It is calculated using Equation (1)

$$K_W = \frac{\sqrt[3]{1.8 \times (T_{50} + 273.15)}}{SG} \quad (1)$$

where

T_{50} = temperature at which 50% of crude oil evaporates, °C;

SG = specific gravity of crude oil at 15.6 °C.

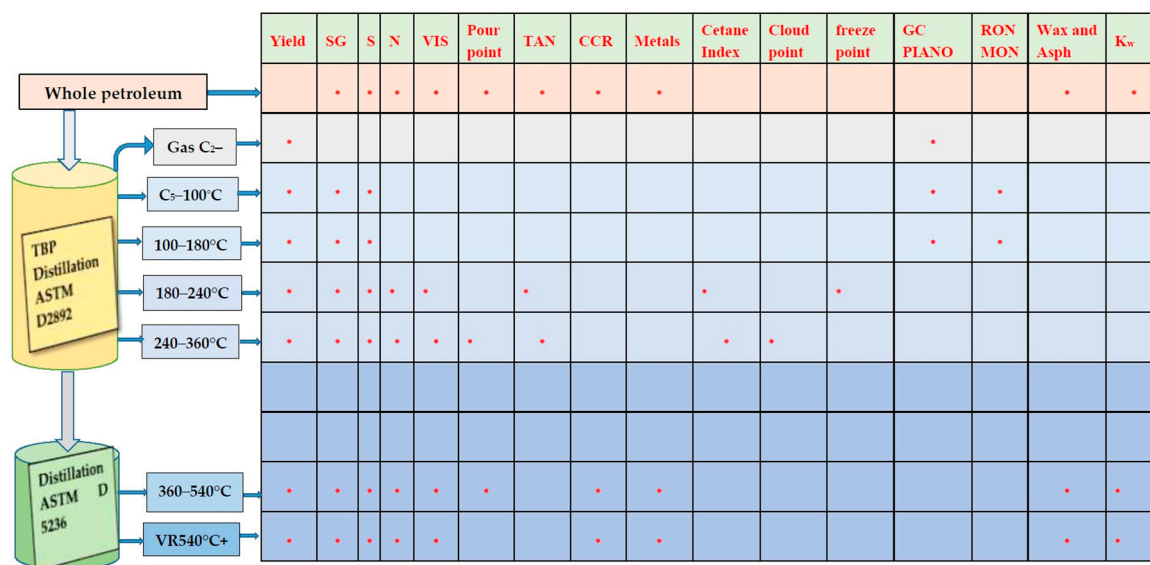


Figure 2. Analytical scheme of crude oil characterization according to the comprehensive assay. Note: SG = specific gravity; VIS = viscosity; CCR = Conradson carbon residue; GC Piano = Gas chromatography paraffins, isoparaffins, aromatics, naphthenes, olefins; RON = research octane number; MON = motor octane number; Asph = asphaltene.

The average K_W values for the three classes of hydrocarbons present in crude oil were calculated by Mohammadi et al. [82] as follows: 12.76 (alkanes); 11.00 (cycloalkanes) and 10.36 (arenes).

Meier et al. [83] proposed a method for characterization of the chemical nature of heavy petroleum oils based on the K_W -characterization factor. They developed three Equations (2)–(4) for predicting aromatic carbon content, aromatic hydrogen content and total hydrogen content of the heavy oil using the characteristics K_W , refractive index and specific gravity.

$$C_a = 134.4679[RI - 1.4750] - 20.4858[K_w - 12.5] \quad (2)$$

$$H_a = 333.471[RI - 1.4750]^2 - 6.687[K_w - 12.5] \quad (3)$$

$$H = -20.77[SG - 0.8510] + 0.58[K_w - 12.5] + 14 \quad (4)$$

where

C_a = wt.% aromatic carbon

H_a = wt.% aromatic hydrogen

H = wt.% total hydrogen

RI = refractive index at 68 °F

SG = specific gravity, density of oil at 60 °F relative to water at 60 °F

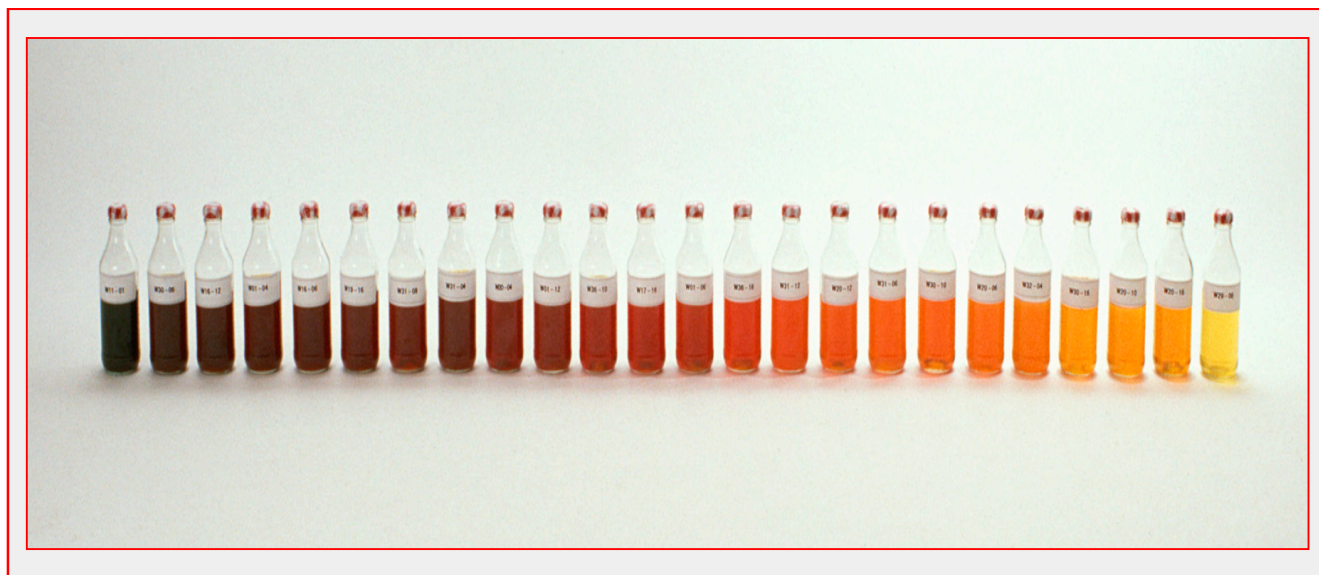


Figure 3. Appearance of the crude oil samples under study.

2.2.2. Bureau of Mines Correlation Index (BMCI) [10,84]

The Bureau of Mines Correlation Index (*BMCI*) can be calculated from *SG* and $T_{50\%}$ (in degrees Celsius) via Equation:

$$BMCI = \frac{48640}{(T_{50} + 273.15)} + \frac{473.7}{SG} - 456.8 \quad (5)$$

The normal paraffin series is defined as having a *BMCI* value of 0, while aromatic compounds are assigned a *BMCI* value of 100. Accordingly, index values between 0 and 15 indicate that paraffin hydrocarbons dominate. Values ranging from 15 to 50 indicate the predominance of naphthenes or mixtures of paraffins, naphthenes, and aromatics. When the index exceeds 50, aromatic compounds are the dominant type.

2.2.3. Specific Gravity and API Gravity [6]

Both specific gravity and *API* gravity measure density relative to water at 60 °F (15.6 °C). *API* gravity is expressed in degrees (°*API*) and can be determined from the specific gravity using the following relationship:

$$API = \frac{141.5}{SG} - 131.5 \quad (6)$$

Table 3 presents the classification of crude oils based on *API* gravity.

2.2.4. Mallison Classification [85]

Mallison categorized crude oils based on the nature of the residuum—the material remaining after the distillation process, particularly with respect to wax content. Crude oil is classified as asphaltic when the distillation residue contains less than 2% wax, whereas it is considered paraffinic when the wax content exceeds 5%. Residue containing more than 5% wax indicates paraffinic crude. Residue with less than 2% wax is classified as naphthenic-based crude. Residue containing 2–5% wax is regarded as mixed-base crude.

Table 3. Classification of crude oils according to *API* gravity.

Classification	Fraction 1 250–270 °C, Atm. Pressure		Fraction 2 275–300 °C, 40 mm Hg	
	<i>API</i> Gravity	Type	<i>API</i> Gravity	Type
Paraffin	>40.0	Paraffin	>30.0	Paraffin
Paraffin–intermediate	>40.0	Paraffin	20.1–29.9	Intermediate
Intermediate–paraffin	33.1–39.9	Intermediate	>30.0	Paraffin
Intermediate	33.1–39.9	Intermediate	20.1–29.9	Intermediate
Intermediate–naphthene	33.1–39.9	Intermediate	<20.0	Naphthene
Naphthene–intermediate	<33.0	Naphthene	20.1–29.9	Intermediate
Naphthene	<33.0	Naphthene	<20.0	Naphthene
Paraffin–naphthene	>44.0	Paraffin	<20.0	Naphthene
Naphthene–paraffin	33	Naphthene	>30.0	Paraffin

2.2.5. Classification by Chemical Composition [25]

A widely recognized and still commonly applied system for classifying crude oils was developed at the U.S. Bureau of Mines by Smith (1927) and later refined by Lane and Garton (1935) [25]. This method relies on distillation data and the specific gravities of two key distillation fractions (250–275 °C and 275–300 °C; see Table 4).

Table 4. Classification of crude oils according Lane and Garton.

Classification	Key Fraction 1 250–275 °C, Atm. Pressure		Key Fraction 2 389–415 °C, Atm. Pressure	
	Specific Gravity	Type	Specific Gravity	Type
Paraffin	≤0.8251	paraffinic	≤0.8762	paraffinic
Paraffin–Intermediate	≤0.8251	paraffinic	0.8767 to 0.9334	intermediate
Intermediate–Paraffin	≤0.8251	paraffinic	≥0.9340	naphthenic
Intermediate	0.8256 to 0.8597	intermediate	≤0.8762	paraffinic
Intermediate–Naphthene	0.8256 to 0.8597	intermediate	0.8767 to 0.9334	intermediate
Naphthene–Intermediate	0.8256 to 0.8597	intermediate	≥0.9340	naphthenic
Naphthene	≥0.8602	naphthenic	≥0.9340	naphthenic
Paraffin–Naphthene	≥0.8602	naphthenic	0.8767 to 0.9334	intermediate
Naphthene–Paraffin	≥0.8602	naphthenic	≤0.8762	paraffinic

Crude oils can also be classified based on their sulfur content. In this context, the proportions of alkanes, naphthenes, and aromatic compounds are determined using currently available analytical techniques. All data relate to the fraction of petroleum that boils above 210 °C at atmospheric pressure. The alkane (paraffin) content includes both normal (n-) and isoalkanes, but excludes alkyl side chains attached to cyclic structures. Cycloalkanes (naphthenes) comprise compounds with one or more saturated rings and no aromatic rings. Aromatic compounds are defined as those containing at least one aromatic ring; these molecules may also have saturated rings or side chains attached to the ring structure. Table 5 presents the classification according to hydrocarbon type and sulfur.

Table 5. Classification of crude oils according hydrocarbon type and sulfur.

Hydrocarbon Group Content in Crude Oil > 210 °C, wt.%		Crude Oil Type	Sulfur Content in Crude Oil (Approximate)	Number of Samples per Class (Total = 541)
Sat > 50 wt.% AA < 50 wt.%	P > <u>Naph</u> and P > 40 wt.%	Paraffinic	<1 wt.%	100 (18.5%)
	P ≤ 40 wt.% and <u>Naph</u> ≤ 40 wt.%	Paraffinic–naphthenic		217 (40.1%)
	<u>Naph</u> > P and <u>Naph</u> > 40 wt.%	Naphthenic		21 (3.9%)
Sat < 50 wt.% AA > 50 wt.%	P > 10 wt.%	Aromatic–intermediate	>1 wt.%	126 (23.3)
	P ≤ 10 wt.%	<u>Naph</u> ≤ 25 wt.% Aromatic–asphaltic		41 (7.6)
		<u>Naph</u> ≥ 25 wt.% Aromatic–naphthenic	Generally S < 1%	36 (6.6%)

Note: Sat = saturates AA = aromatics + resins + asphaltenes; P = paraffins; Naph = naphthenes.

According to this specification, crude oils are described as “paraffinic” or “naphthenic” when saturated hydrocarbons constitute more than 50% of their composition. For practical application—particularly in geological contexts—additional limits of 40% are applied to alkanes and cycloalkanes. These thresholds distinguish fully paraffinic oils from intermediate paraffinic–naphthenic types, separating them further from naphthenic oils. Crude oils are classified as “aromatic” when saturated hydrocarbons constitute less than 50% of the composition, implying that aromatics, resins, and asphaltenes collectively exceed 50%. Based on alkane content, a further distinction is made between “aromatic–intermediate” oils (containing more than 10% normal and isoalkanes) and heavily degraded oils (with less than 10%). The latter group is subdivided into: “Aromatic–asphaltic” oils (containing less than 25% naphthenes) and “Aromatic–naphthenic” oils (containing more than 25% naphthenes). This subdivision also reflects differences in sulfur content: aromatic–asphaltic oils are typically high in sulfur, whereas aromatic–naphthenic oils generally contain less than 1% sulfur.

2.2.6. Classification of Oils by Physicochemical Properties [86]

Table 6 shows the classification of crude oils based on the physicochemical properties.

Table 6. Classification of crude oils by physicochemical properties.

Property	Oil Class		Limits of Change in Classification Intervals
Density, g/cm ³	Very light		Less than 0.80
	Light		0.80–0.84
	With medium density		0.84–0.88
		With increased density	0.88–0.92
	Heavy	Extra heavy Bituminous	0.92–0.96 More than 0.96
Viscosity at 20 °C, mm ² /s	Low viscosity		Less than 10
	Medium viscosity		10–35
		With increased viscosity	35–100
	Viscous	Highly viscous Extra viscous	100–500 More than 500
Sulfur content, wt.%	Low sulfur		Less than 0.5
	Medium sulfur		0.5–1
	Sour		1–3
	High sulfur		More than 3

Table 6. *Cont.*

Property	Oil Class		Limits of Change in Classification Intervals
Resin content, wt. %	Slightly resinous		Less than 8
	Medium resinous		8–13
	Resinous	Moderately resinous	13–20
		Highly resinous	20–30
		Ultrahighly resinous	More than 30
Asphaltene content, wt. %	Low asphaltenic		Less than 3
	Medium asphaltenic		3–10
	Highly asphaltenic		More than 10
Wax content, wt. %	Low wax		Less than 1.5
	Medium wax		1.5–6
	Waxy	Moderately waxy	6–10
		Highly waxy	10–20
		Ultrahighly waxy	More than 20
Amount of IBP—200 °C fraction, wt. %	Low content		Less than 15
	Medium content		15–30
	High content		More than 30
Amount of IBP—300 °C fraction, wt. %	Low content		Less than 30
	Medium content		30–50
	High content		More than 50
Amount of IBP—350 °C fraction, wt. %	Low content		Less than 45
	Medium content		45–57
	High content		More than 57
Gas saturation of oil, m ³ /t	With low gas saturation		Less than 200
	With medium gas saturation		200–500
	With high gas saturation		More than 500
Hydrogen sulfide content, wt. %	With low content		Less than 5
	With high content		More than 5
Vanadium content, wt. %	With low content		Less than 0.003
	With high content		More than 0.003
Nickel content, wt. %	With low content		Less than 0.007
	With high content		More than 0.007

2.2.7. Classification Based on Geochemical Concepts [69]

Frans van den Berg et al. [69] proposed a classification of crude oils based on the geochemical framework as shown in Figure 4. This method is based on the van Krevelen diagram, introduced in 1950 [87], which depicts atomic H/C and O/C ratios visualizing the process of coal formation [88,89]. Table 7 presents the effect of source rock kerogen on the properties of crude oil.

Maturity of the studied crude oils was quantified using the H-factor (heaviness factor) proposed by van den Berg et al., which is a proprietary measure of maturity [69]. According to the method proposed by van den Berg et al., crude oils with an H-factor lower than 885 are considered mature, those with H-factor between 885 and 920 are considered intermediate, while crude oils having H-factor higher than 920 are regarded as immature [90].

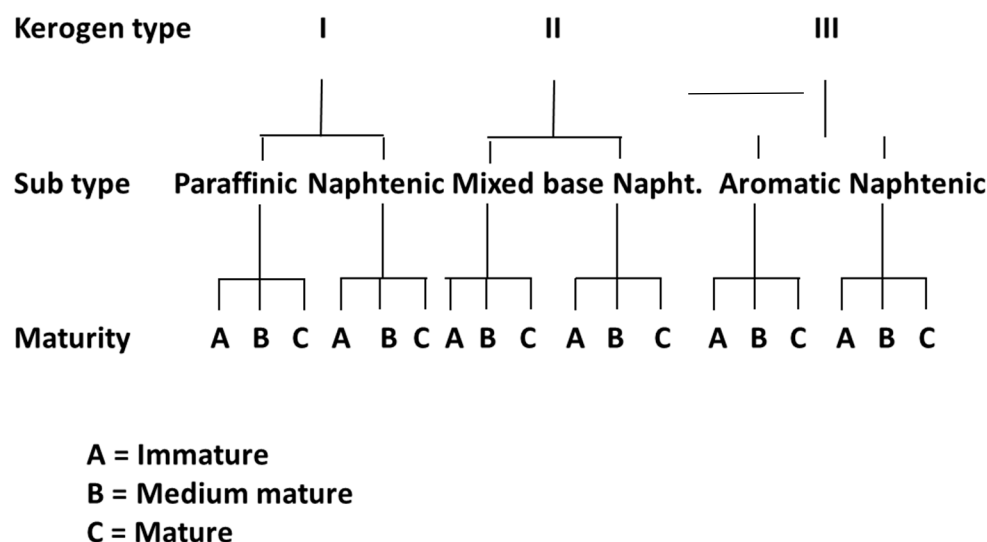


Figure 4. Classification based on geochemical concepts.

Table 7. Effect of kerogen type on crude oil properties.

Kerogen Type	Origin	Sulfur Content	Oxygen Content	Chemical Type
I	Plant material, deposited under <u>anaerobic</u> conditions in a lacustrine (sweet)/marine (seawater) environment Highly oil prone	Low	Low	Paraffinic $Ni > V$
II	Bacterial/algal material, deposited under anaerobic/aerobic conditions, in a marine environment Oil prone	High	Medium	Aromatic/ Naphthenic $V > Ni$
III	Land-based biomass, deposited under aerobic conditions, lacustrine/terrigenous environment Gas prone	Low	High	Aromatic Low in metals

2.2.8. Classification of Crude Oils According to GOST P 51858-2020 [21]

Russian state standard GOST P 51858-2020 defines the classification of crude oils as shown in Tables 8–11 and Figure 5.

Depending on the degree of preparation, oil is divided into groups 1–3, the requirements for which are given in Table 10.

Depending on the content of hydrogen sulfide, methyl and ethyl mercaptans, oil is divided into 2 types, the requirements for which are given in Table 11.

Table 8. Classification of crude oil depending on the sulfur content.

Crude Oil Type Class	Type	Sulfur Content, % m/m	Test Method
1	Low sulfur	<0.6	GOST P 51947, GOST 32139
2	Sulfur	0.60 ÷ 1.80	
3	High sulfur	1.80 3.50	
4	Extra high Sulfur	>3.50	

Table 9. Classification of crude oils by types.

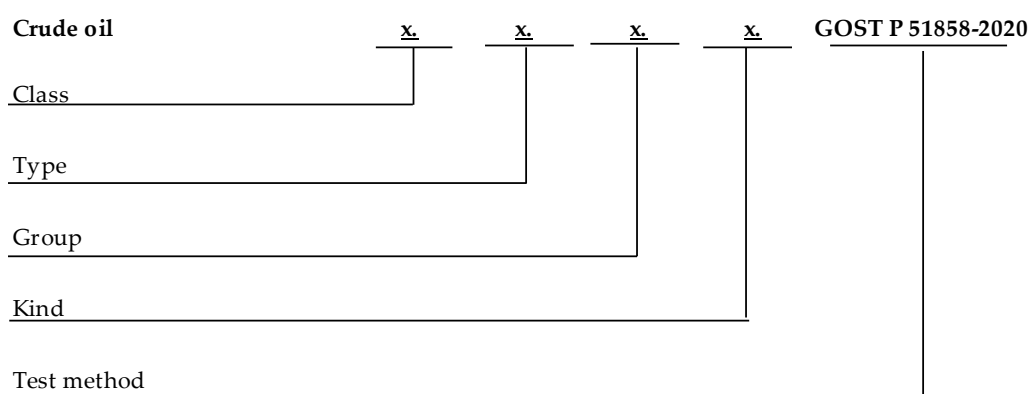
Property	Crude Oil Type					Test Method
	0	1	2	3	4	
Density, kg/m ³ at 20 °C and 15 °C	≤830.0 and ≤833.7	830.1–850.0 and 833.8–853.6	850.1–870.0 and 853.7–873.5	870.1–895.0 and 873.6–898.4	>895.0 and >898.4	GOST 3900 GOST P 51069, GOST 33364, GOST ISO 3675
Distillation recovery, vol%						GOST 2177 (method B)
200 °C	30	27	21	-	-	
300 °C	52	47	42	-	-	
Paraffins, wt.%,			<6.0			GOST 11851

Table 10. Crude oil indices depending on the degree of preparation.

Property	Crude Oil Type			Test Method
	1	2	3	
Water content, wt.%	<0.5	<0.5	<1.0	GOST 2477, GOST 33733
Chloride salt, mg/dm ³	<100	<300	<900	GOST 21534
Mechanical impurities, wt.%		<0.05		GOST 6370

Table 11. Crude oil indicators depending on the content of hydrogen sulfide, methyl and ethyl mercaptans.

Property	Crude Oil Type		Test Method
	1	2	
H ₂ S, ppm	<20.0	<100.0	GOST P 50802,
Methyl and ethyl mercaptan in their blend, ppm	<40.0	<100.0	GOST 32918, GOST 33690

**Figure 5.** Conditional designation of crude oil according to GOST P 51858-2020 [21].

The conventional designation of crude oil shall consist of the word “Crude oil,” four digits corresponding to the class, type, group, and grade designations, and the designation of this standard. When supplying oil for export, the letter “e” is added to the type designation. The structure of the conventional designation of oil is depicted in Figure 5.

2.2.9. Classification of Crude Oils Based on the Contents of Sulfur and Nitrogen, and Total Acid Number [18]

Table 12 presents the classification of crude oils based on the contents of sulfur and nitrogen, and total acid number.

Table 12. Classification of crude oils based on the contents of sulfur and nitrogen, and total acid number [18].

Data Source	Limits	Class
Sulfur content	<0.5 wt. %	Sweet
	≥0.5 wt. %	Sour
Total nitrogen content	<0.25 wt. %	Nitrogen poor
	≥0.25 wt. %	Nitrogen rich
Total acid number	≤0.5 mgKOH·g ^{−1}	Non-acid
	greater than 0.5 and ≤1 mgKOH·g ^{−1}	Acid
	Greater than 1 mgKOH·g ^{−1}	High acid

2.2.10. Miscellaneous Concepts of Petroleum Classifications Reported in the Literature [18–20,22–24,63,91–109]

In addition to the crude oil classification methods discussed in Sections 2.2.1–2.2.9, this subsection summarizes some other classification approaches published in 23 studies, some of which apply various artificial intelligence (AI) techniques based on machine learning. A common feature among some of the approaches discussed in this subsection is the use of chemometric analysis of physical, spectroscopic, or chromatographic data. These chemometric analyses were conducted to categorize the studied crude oils into different groups. They are discussed below.

A scientific team from Brazil [18] integrated mid-infrared (MIR) and near-infrared (NIR) spectroscopy of 121 crude oil samples from the Brazilian sedimentary coastal basin through low-level and mid-level data fusion and thus improved the classification of crude oil samples into categories based on sulfur content, total nitrogen content, total acid number and API gravity. This approach offers a promising alternative to traditional laboratory analyses by providing rapid, accurate, and cost-effective discrimination of crude oils. While additional information on validation and dataset characteristics would strengthen the study, the reported results suggest that data fusion combined with chemometric techniques such as Partial Least Squares Discriminant Analysis (PLS-DA) can significantly enhance analytical performance in petroleum characterization.

Other scientists from Iranian and Spanish universities [19] investigated the use of attenuated total reflectance Fourier transform infrared (ATR-FTIR) spectroscopy combined with chemometric techniques to identify the geological origin of 251 crude oil samples from different Iranian petroleum fields. The study evaluates several multivariate classification methods and concludes that Soft Independent Modeling of Class Analogy (SIMCA) is the most effective approach for discriminating crude oils according to their source. The proposed methodology is presented as a rapid, cost-effective, environmentally friendly alternative to conventional characterization techniques. These results indicate excellent classification performance and suggest that mid-infrared spectra contain sufficient geochemical information to distinguish oils from different reservoirs. The study also reports successful classification of mixture samples in several cases, indicating practical applicability beyond pure crude oils.

ATR-FTIR spectroscopy combined with chemometric techniques [20] is also applied for the determination and classification of crude oils based on API gravity. Since API gravity is a key parameter used to classify crude oils as light, medium, or heavy and influences refining processes, transportation, pricing, and environmental considerations,

the development of rapid and non-destructive analytical methods for its determination is of significant industrial importance. Specifically, the authors compare Partial Least Squares Regression (PLS-R) and Support Vector Machine Regression (SVM-R) for predicting API gravity and employ PLS-DA for crude oil classification.

Behrenbruch and Dedigama [22] propose a mathematical characterization method for crude oil TBP distillation curves using a two-parameter gamma distribution model. TBP curves represent how crude oil fractions boil off with increasing temperature and act as a compositional “fingerprint” of crude oils. Their study aims to replace or complement traditional qualitative interpretation of TBP curves with a compact, quantitative representation that can support classification, property prediction, and valuation of crude oils. The two interpretable parameters (α and β) of gamma distribution model are linked with important crude oil properties such as API gravity and UOP K factor and thus related to classification of crude oils. It is also shown how crude oil cut fractions may be classified with the aid of a ternary diagram, and the link between this approach and the characterization parameters of gamma distribution model.

Zhou et al. [23] present a portable, low-cost hardware for oil classification that combines capacitance measurements from capillary flow in microfluidic thread-based analytical devices (μ TADs) with machine learning techniques, specifically Linear Discriminant Analysis (LDA). The system is designed for rapid, on-site identification of 8 types of petroleum oil samples provided by China University of Petroleum, Beijing, and 7 types of non-petroleum oil samples purchased from Taobao as an alternative to conventional laboratory-based techniques such as gas chromatography (GC) and mass spectrometry (MS).

Peinder [24] proposes a flexible approach for crude oil classification that systematically evaluates six spectroscopic techniques—infrared (IR), NIR, Raman, ultraviolet-visible (UV-Vis), proton nuclear magnetic resonance (^1H -NMR), and asph (^{13}C -NMR)—combined with chemometric principal component analysis (PCA) and Partial Least Squares (PLS) modeling. The ultimate goal is to replace or supplement conventional ASTM/IP crude oil analyses with rapid spectroscopic measurements, aiming at the prediction of physicochemical properties directly from spectra. Consequently, classification can be derived from the predicted values. Among all techniques, IR spectroscopy proved to be the most reliable and practical. The strongest prediction models were obtained for long-residue yield, density and viscosity. These properties are among the most important indicators used in crude oil classification and valuation. Prediction of sulfur content, asphaltenes, carbon residue was less accurate but still useful for screening purposes. This suggests that IR spectroscopy coupled with PLS modeling can predict many critical crude oil properties with accuracy comparable to standard ASTM/IP methods, while requiring significantly less time and effort.

Iranian researcher Mohammadi [63] focused on one of the most important properties for crude oil classification: sulfur content, which is the basis for distinguishing sweet crude oils from sour crude oils. The study proposes a rapid analytical framework using ATR-FTIR spectroscopy combined with chemometric techniques such as PLS-R and SVM-R for both quantitative determination of sulfur concentration and qualitative classification of crude oils into sweet and sour categories, which is directly relevant to refinery economics, catalyst performance, environmental compliance, and crude oil pricing.

Niu et al. [91] investigated how measuring the content and distribution characteristics of trace elements, among which 20 trace element-related parameters such as V/Ni, Co/Ni, U/Th, of 30 crude oils and using cluster analysis the crude oils in the study area could be divided into 3 types. The investigated crude oils have a wide range of density and viscosity, with the density range from 0.82 g/cm³ to 0.99 g/cm³ and the viscosity range from 2.94 mPa s to 4861 mPa s. The wax content and sulfur content in the analyzed

samples reached the maximum values of 40.84% and 2.79%, respectively. The total amount of trace elements showed good negative correlation with relative content of saturated hydrocarbons, and a positive relationship with relative content of aromatic hydrocarbons. The total amount of elements and the relative content of resins and asphaltenes also have a good positive correlation. Different types of crude oil have obvious differences in element content and related parameters.

A Mexican study [92] presents a Fourier transform infrared (FTIR)-based classification method for determining the geological origin and maturity history of crude oils. This work focuses on a fundamental petroleum geochemistry problem: distinguishing oils according to their depositional environment and post-generation alteration processes. The authors classify petroleum into four categories: marine origin, non-marine origin, degraded petroleum and thermally transformed petroleum. The classification is based on the relative abundance of selected aliphatic, aromatic, and polar functional groups measured by FTIR spectroscopy and analyzed using hierarchical clustering and discriminant analysis.

Tao et al. [93] proposed chemometric classification of crude oils using t-distributed stochastic neighbor embedding a machine learning algorithm. They took into account the complex geochemical characteristics of the crude oil precursors and applied machine learning approach to determine crude oil origins in a complex petroleum system. Employing 13 biomarker indicators, such as the ratios C_{29}/C_{30} and $C_{34}S/C_{35}S$ hopanes, the pristane/phytane (Pr/Ph), the abundance of β -carotane, the gammacerane/ C_{30} hopane ratio, β -carotane/n-Ci ratios, Pr/n-C₁₇ vs. Ph/n-C₁₈, and regular C_{27} – C_{29} steranes, measured in 43 crude oils, they classified petroleum precursors into three geochemical subcategories: (1) argillaceous rocks deposited in brackish water and a weakly reducing environment; (2) dolomitic mudstones deposited in saline water and a reducing environment; (3) argillaceous dolomites deposited in hypersaline water and a strongly reducing environment. The t-distributed stochastic neighbor embedding (t-SNE) algorithm was found to correlate with the three types of source rocks and the crude oils. Thus, by using the t-SNE machine learning algorithm the complex origins and occurrences of crude oil in the studied area were identified.

Chiaberge et al. [94] demonstrated how ultra-high-resolution mass spectrometry (UHRMS) coupled with chemometric data analysis can classify crude oil samples based on their geographical origin and extraction well. The authors claimed that their approach combined with statistical techniques can effectively facilitate reservoir monitoring and optimization for oil extraction.

Asif and Fazeelat [95] utilizing the distribution of alkylnaphthalenes, alkylphenanthrenes, alkyl dibenzothiophenes, alkyl dibenzofurans, alkylfluorenes, alkylbiphenyls, triaromatic steroids, methyl triaromatic steroids, retene, methyl retenes and cadalene, determined in 18 crude oils, classified them into three groups (A, B, and C). Group A is derived from higher plant resin, while Groups B and C are marine crude oils. Group B features an abundance of S-containing heterocyclic aromatic hydrocarbons, while Group C is characterized by an abundance of alkylfluorenes in conjunction with S heterocyclic compounds.

Zhao et al. [96] noted that the classification of crude oil based on API gravity and SARA composition is not sufficiently informative in the process of heavy oil development. For this reason, they introduced the concept of average carbon number (ACN). ACN has been shown to be a simple and accurate indicator that takes into account the molecular weight, polarity, structure and flow behavior of crude oil and can serve not only as a theoretical tool for crude oil characterization, but also as an application guide for viscosity reduction, diluent screening and heavy oil upgrading strategies.

Sun et al. [97] applied chemometric analysis to classify 300 oils including 12 light fuel oils, 104 heavy fuel oils, and 184 crude oil samples based on the mass chromatogram

m/z 256 using the combination of PCA and LDA. The m/z 256 mass chromatograms normalized and aligned by correlation optimized warping (COW) were analyzed by PCA, which converts the original data into a set of linearly independent representations of each dimension through a linear transformation, while preserving as much information from the original data sets as possible. Five principal components from the PCA evaluations were used in the LDA; for the training set (172 samples), and for the test set (128 samples). A good regression model with three discriminant equations for heavy fuel oils, light fuel oils and oils was obtained. This method was found effective for identification and classification of crude oils and refined finished products.

Wang et al. [98] utilized a systematic geochemical analysis of biomarker ratios of 37 crude oil samples, 21 oil sand samples, and 23 sandstone samples from four oilfields and applying chemometrics, established in 1970 as a chemistry discipline, integrating statistics, numerical analysis, applied mathematics, and computer science [99–101] to classify oils into four families. The chemometric methods employed to unravel the relationships between studied crude oils and prospective source rocks consisted of PCA, hierarchical cluster analysis (HCA), t-SNE and uniform manifold approximation and projection (UMAP) algorithm. The nonlinear dimensionality reduction methods such as t-SNE and UMAP proved their capability as useful tools to classify crude oils.

Sancho et. al. [102] attempted to provide the optimal categorization for crude oils using k-means clustering. The study evaluates six physicochemical properties rather than just traditional density and sulfur metrics, namely: pour point, acidity, Conradson carbon content, nickel content, vanadium content and iron content. This framework utilizes an industrial refinery dataset published on ScienceDirect to improve downstream operations via optimizing refining operations, predicting oil behavior when refinery operators have to process unknown crude and improving blending decisions.

Galtier et al. [103] evaluated different statistical methods to classify crude oils and virgin olive oils using infrared spectroscopy. The researchers compared four chemometric modeling methods—SIMCA, PLS1-DA, PLS2-DA, and PLS2-DA-SIMCA—to see which best determines the geographical origin of samples. They tested 36 samples from 36 crude slates from Algeria, South America, Equator, and Venezuela using MIR spectroscopy. The study concluded that PLS1-DA is the most efficient and suitable tool for geographic classification via spectral data. The authors concluded that determining the variance ratio against the Fisher Criterion might be an excellent benchmark for selecting the ideal wavelength ranges to analyze.

Sarafdokht et al. [104] argued that conventional crude oil classification methods concentrate on certain features and neglect others. To overcome these limitations of classical crude oil classification methods, they proposed an innovative chemometric method that integrated the techniques of modified moving window correlation coefficient (MMWCC), multidimensional scaling (MDS), and HCA to classify 93 crude oil samples based on their asphaltene structural features. It was found that geochemical characteristics influence the structural characteristics of asphaltenes, while differences in migration pathways have a negligible effect. Therefore, the defined groups provide valuable information about genetic types and oil deposits in studied Dezful Bay area.

Barwise [105] investigated the role of nickel and vanadium in the classification of crude oil. He examined families of crude oils from several basins around the world and categorized them into five classes (A, B, C, D, E). Classes A (Middle East-the Gulf of Suez and Abu Dhabi), B (North Sea), and C (China) are assigned as being generated from aquatic organic matter, but differ in the degree of sulfur incorporated into the kerogen. Classes D (Indonesia) and E (Australia) are identified as being obtained primarily from terrestrial plants. The Australian class represents organic matter derived from a “classical”

contribution from terrestrial plants, while the Indonesian class differs in having a greater contribution from resinous material. Barwise [105] inferred that the source rocks, which are immature and have a low clay content and a high organic sulfur content such as carbonate source rocks, generate crude oils with the highest metal content. Marine shales or lacustrine source rocks produce crude oils with moderate amounts of metals, while land-plant-generated crude oils have a very low content of nickel and/or vanadium. Nickel/vanadium ratio lower than 1 was found typical for marine sourced crude oils, while when this ratio is higher than 1, crude oils are generated from lacustrine source rocks.

Sokolova et al. [106] proposed a chemical classification of naphthenic condensates based on a study of the composition of 21 naphthenic condensates from different deposits located in the northern part of Western Siberia. The condensates are divided into seven chemical types (A1, A2, B1t, B1b, B1m, B2c and B2i). Condensates of types A-1 and A-2 contain n-alkanes and their hydrocarbon compositions are close to those of the C₆–C₁₃ fractions of the corresponding crude oils. Condensates B-2i and B-2c are distinguished by their content of isoprenoid alkanes. Condensates B-1 are quite different. They contain insignificant amounts of n-alkanes and isoprenoid alkanes and include members with very high contents of monocyclic (B-1m), bicyclic (B-1b) and tricyclic (B-1t) compounds. The similarity between the composition of condensates and the C₆–C₁₃ fraction of crude oils suggests that condensates and crude oils are genetically close and condensates can be considered as petroleum derivatives formed as a result of the dissolution of light fractions in compressed gas.

Yuhan et al. [107] classified crude oils into four different groups based on the analysis of saturate and aromatic fractions of 41 crude oils using gas chromatography-mass spectrometry (GC-MS) and applying multivariate statistical analysis. They used Eward's hierarchical clustering method with squared Euclidean distance as the similarity measure and setting a threshold distance of ten for cluster distinction and PCA to analyze the biomarker parameters diterpanes/nC₂₀, Pr/nC₁₇, Ph/nC₁₈, Pr/Ph, diadrimane/8β(H)-drimane, 8β(H)-drimane/8β(H)-homodrimane, 4β(H)-19-norisopimarane/isopimarane, 16β(H)-phylocladane/isopimarane, 1,2,5-trimethylnaphthalene/1,3,6-trimethylnaphthalene, 1,7-dimethylphenanthrene/phenanthrene, retene/phenanthrene, as well as the δ¹³C_{oil} with the aim to classify the studied crude oils. The four types are categorized based on the different inputs from ferns, gymnosperms, and angiosperms.

Meng et. al. [108] investigated molecular geochemical characteristics of crude oil and identified oil–source rock relationships within the Hexiwu structural belt of the Langgu Depression, Bohai Bay Basin, China. The researchers categorized the studied crude oils into three distinct genetic types by evaluating molecular biomarkers and geochemical parameters: Type I—Mature Crude Oils distributed mostly across the northern and central segments of the structural belt; Type II—Mixed-Source Oils found in the southern Hexiwu area; and Type III—Mature Crude Oils concentrated in the south of the structural belt. The outcomes of the study shown successfully established a dual-source hydrocarbon supply framework for the Hexiwu basin. Definition of these three reservoir types resolves long-standing oil–source ambiguities and provides critical theoretical guidance for future crude oil upstream activities.

Barbosa et al. [109] used NIR spectroscopy methods, together with PLS-DA and SVM to classify a set of 196 crude oil samples from the Brazilian sedimentary coastal basin as light, medium, heavy, sweet, sour, non-sour, and sour. They showed that PLS-DA, SVM, and SVM ensemble methods used for NIR spectroscopy data analysis can be considered as useful tools for categorizing crude oil samples.

Approaches based on the similarity between the reference indices of benchmark crude oils and the crude oil samples under study, as assessed using various statistical

and machine learning methods, offer an interesting alternative to classical classification methods, enabling the differentiation of crude oils based on various classification criteria. This manner of crude oil characteristic data evaluation will be applied in this research as well, using the intercriteria analysis approach that will be discussed later in this article.

2.2.11. Summary of Reviewed Classifications of Petroleum

The classifications of petroleum discussed in Sections 2.2.1–2.2.10 can be graphically summarized as shown in Figure 6.

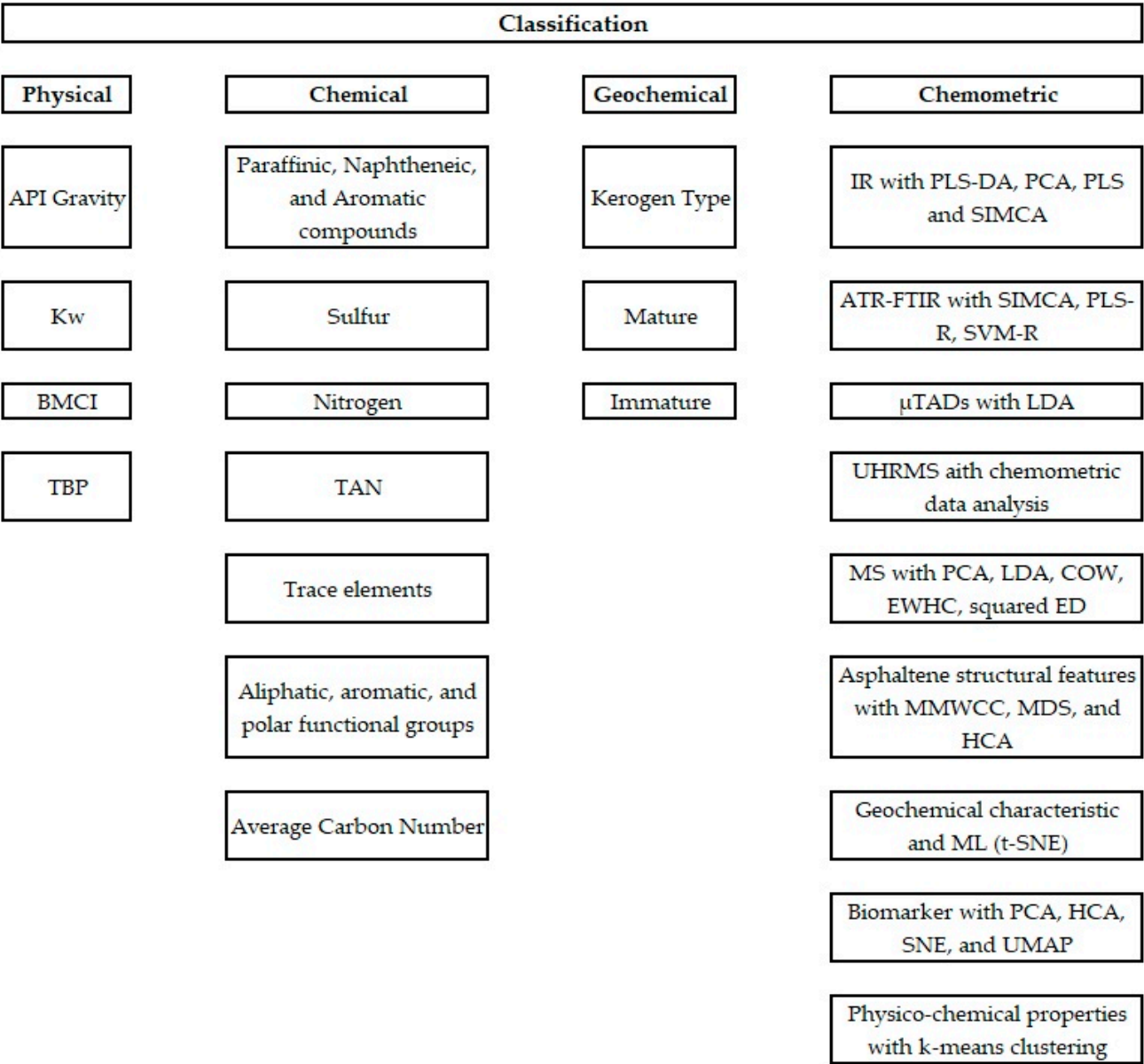


Figure 6. Summarization flow chart of the reviewed classifications of petroleum discussed in Sections 2.2.1–2.2.10.

All classification methods developed for the period 1950–2003 are based on defined ranges of specific values for certain petroleum characteristics, classified as physical, chemical, and geochemical. In the 21st century, a new classification approach called chemometrics was proposed, which combines the characteristics of petroleum, including physicochemical, geochemical, spectral, and chromatographic, with the application of mathematical, statistical, and computational techniques to chemical data. Chemometric classifications are useful

in oil spill source identification [110–113], for geographic origin determination [114], for development of oil–source correlations [115], and others. However, chemometric methods yet to be used for crude oil selection purposes have not yet been published.

2.3. Petroleum Refinery Performance Used to Classify Crude Oils

The performance of the oil refinery under study, which is considered one of the most complex refineries in the world according to the Solomon Associates Fuel Study, was used as the basis for classifying the different types of crude oil. The processing scheme of the refinery is depicted in Figure 7. The refinery consists of two Crude Distillation Units (CDUs)—CDU-1 and CDU-2, which fractionate the incoming crude oil into dry gas, liquefied petroleum gas (LPG), light naphtha (fraction 30–100 °C), heavy naphtha (fraction 100–180 °C), kerosene fraction (fraction 180–240 °C), diesel fraction (fraction 240–360 °C), atmospheric gasoil (fraction 360–480 °C) and atmospheric residue (fraction > 360 °C; fuel oil). The vacuum distillation unit the CDU-1 fractionates the atmospheric residue into light vacuum gasoil (fraction 240–360 °C), heavy vacuum gasoil (fraction 360–540 °C), and vacuum residue (fraction > 540 °C).

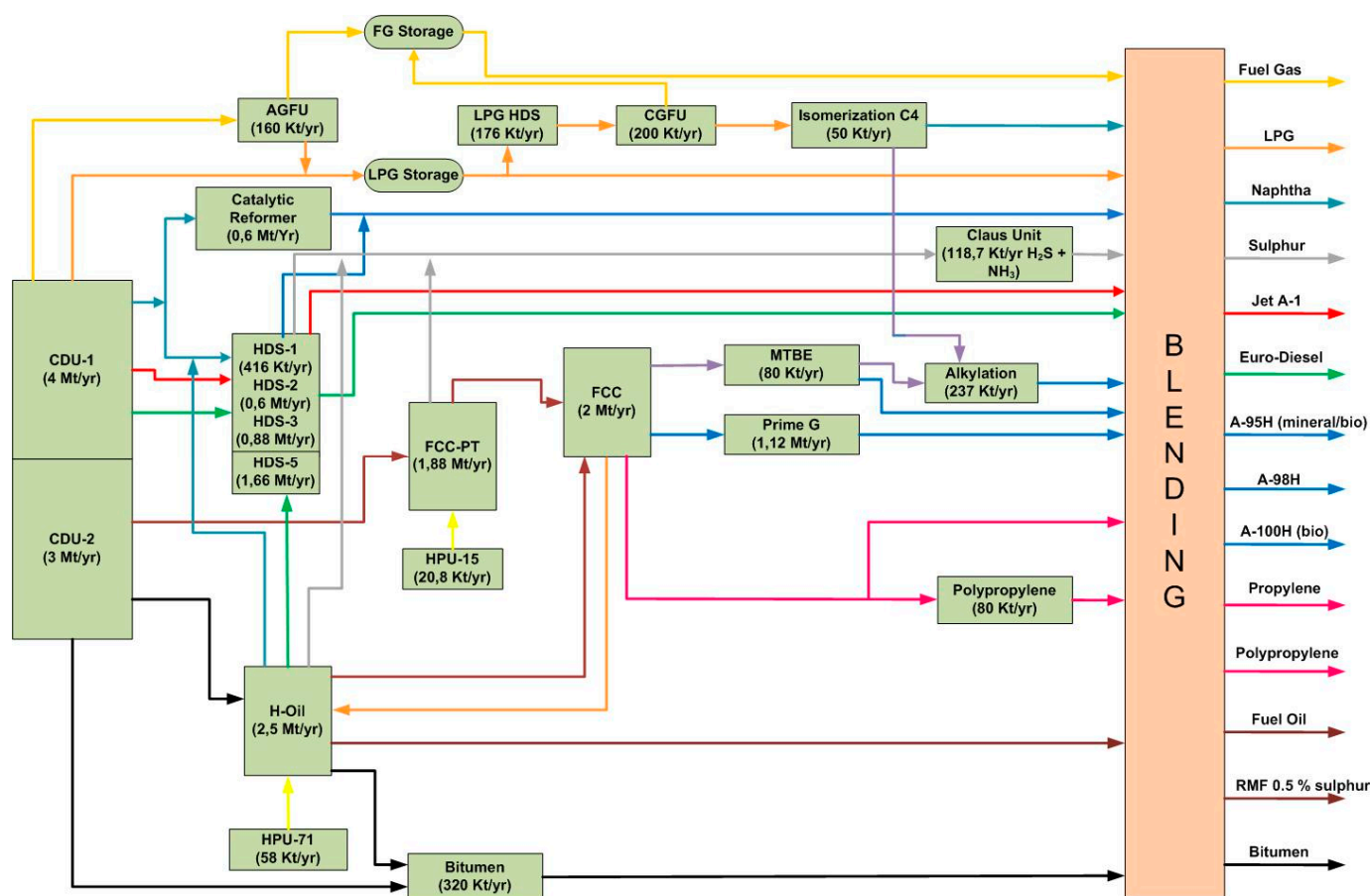


Figure 7. Processing diagram of refinery under study.

The vacuum distillation unit of the CDU-2 fractionates the atmospheric residue obtained from the atmospheric section of CDU-2 into identical fractions as produced by the vacuum distillation unit of CDU-1. All of the above-mentioned fractions obtained from crude oil distillation are processed simultaneously in other refining units, as follows:

- The dry gas is processed in the hydrocarbon gas absorption fractionation unit (AGFU);
- LPG is processed in the central gas fractionation unit (CGFU);

- Light naphtha is upgraded in the Hydrodesulphurization unit 1 (HDS-1), where the sulfur content is reduced to below 10 ppm, while heavy naphtha is upgraded in the Catalytic Reformer, where its octane number is increased from 55 to 100;
- The kerosene fraction is refined in the HDS-2 unit, where the sulfur content is reduced from about 2000 ppm to below 10 ppm;
- The diesel fraction is refined in both units HDS-3 and HDS-5; where the sulfur content of the diesel fraction is reduced from about 10,000 ppm to below 10 ppm;
- The atmospheric gas oil is upgraded in the Fluid Catalytic Cracking (FCC) feed Pretreater (FCC-PT);
- The vacuum residue is hydrocracked in the Ebullated Bed H-Oil unit.

2.4. Intercriteria Analysis as a Tool for Classifying Crude Oils Based on Refinery Performance and Crude Oil Characteristics

The characteristics of crude oils, whose processing in the refinery under study is affected by operational issues such as high acidity of sour water in CDUs, the related high corrosion rate [74,116], high fouling rate in H-Oil unit [74,117,118], H-Oil reactor instability (which can trigger an emergency shutdown) [75], crude oil incompatibility issues [119], were evaluated by intercriteria analysis (ICrA) to determine the extent of similarity. ICrA is a new mathematical method, similar to, but also significantly different from, correlation analysis. It is capable of quantifying the degree of similarity between different objects (including, in particular, petroleum fluids) based on predefined criteria (including oil characteristics). ICrA is based on the ideas of intuitionistic fuzzy sets [120] and index matrices [121]. Details of the mathematical basis of ICrA are given in [122,123]. In addition to petroleum chemistry and processing, ICrA currently finds applications in biology [124], medicine [125–127], ecology [128], economics [129–131], and other fields [132–134].

Following [120], we will mention that in mathematical terms, set A is defined as an IFS as:

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle \mid x \in X \},$$

where X is the universum, and the two mappings $\mu_A(x), \nu_A(x): A \rightarrow [0, 1]$ are respectively the degree of membership and the degree of non-membership of each element $x \in X$, such that $0 \leq \mu_A(x) + \nu_A(x) \leq 1$. The boundary conditions are 0 and 1, both giving the classical set.

The ICrA approach uses as an input a two-dimensional (2D) IM, representing a set of indices of the rows, a set of indices of the columns, and a set of elements corresponding to each pair of row and column index. In the case of ICrA, the IM can be written as $[O, C, e_{o,c}]$, where O and C are respectively the set of row and column indices, O stands for objects, C stands for criteria, and $e_{o,c}$ corresponds to the evaluation of each object O against the criterion C . If we denote by m the number of objects, and by n the number of criteria, the input IM for ICrA can be represented as follows:

	C_1	...	C_k	...	C_n
O_1	e_{O_1,C_1}	...	e_{O_1,C_k}	...	e_{O_1,C_n}
...	...	...	...	...	...
O_i	e_{O_i,C_1}	...	e_{O_i,C_k}	...	e_{O_i,C_n}
...	...	...	...	...	...
O_m	e_{O_m,C_1}	...	e_{O_m,C_k}	...	e_{O_m,C_n}

In the next step of ICrA relations are formed between every two elements of the matrix, thus the evaluations of the criteria are compared in pairs for all objects in the matrix (Figure 8).

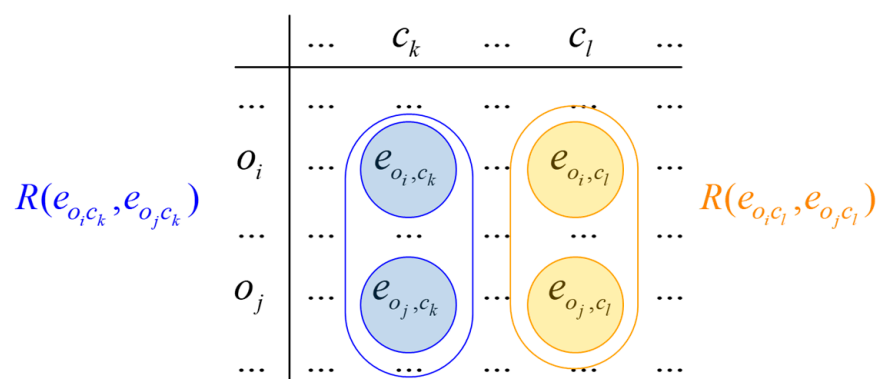


Figure 8. Formation of relations in ICRA.

Following [119], we define that the relation $R(e_{O_i, C_k}, e_{O_j, C_k})$ has dual relation $\bar{R}$, which is true in the cases when relation R is false, and vice versa. Two intuitionistic fuzzy counters $S_{k,l}^\mu$ and $S_{k,l}^\nu$ are formed and are incremented based on the following rules:

- $S_{k,l}^\mu$ is the number of cases, in which the relations $R(e_{O_i, C_k}, e_{O_j, C_k})$ and $R(e_{O_i, C_l}, e_{O_j, C_l})$ (or the relations $\bar{R}(e_{O_i, C_k}, e_{O_j, C_k})$ and $\bar{R}(e_{O_i, C_l}, e_{O_j, C_l})$) are simultaneously satisfied.
- $S_{k,l}^\nu$ is the number of cases, in which the relation $R(e_{O_i, C_k}, e_{O_j, C_k})$ and $\bar{R}(e_{O_i, C_l}, e_{O_j, C_l})$ (or the relations $\bar{R}(e_{O_i, C_k}, e_{O_j, C_k})$ and $R(e_{O_i, C_l}, e_{O_j, C_l})$) are simultaneously satisfied.

The total number of pairwise comparisons between the evaluations of m objects is $m(m-1)/2$, therefore $0 \leq S_{k,l}^\mu + S_{k,l}^\nu \leq \frac{m(m-1)}{2}$.

For every k, l ($1 \leq k \leq l \leq m$ and $m \geq 2$), two normalized values are obtained from the above counters:

- $\mu_{C_k, C_l} = 2 \frac{S_{k,l}^\mu}{m(m-1)}$, called the *degree of agreement* in terms of ICRA, and
- $\nu_{C_k, C_l} = 2 \frac{S_{k,l}^\nu}{m(m-1)}$, called the *degree of disagreement* in terms of ICRA.

The pair $\langle \mu_{C_k, C_l}, \nu_{C_k, C_l} \rangle$ constructed from these two numbers is called an intuitionistic fuzzy pair (IFP) and plays the role of intuitionistic fuzzy evaluation of the relation between any two criteria C_k and C_l . The number $1 - \mu_{C_k, C_l} - \nu_{C_k, C_l} \in [0, 1]$ determines the degree of uncertainty of the IF evaluation.

The output IM puts together all these intuitionistic fuzzy pairs, as follows:

	C_1	...	C_k	...	C_n
C_1	$\langle 1, 0 \rangle$	...	$\langle \mu_{C_1, C_k}, \nu_{C_1, C_k} \rangle$	...	$\langle \mu_{C_1, C_n}, \nu_{C_1, C_n} \rangle$
...	...	...	...	...	...
C_k	$\langle \mu_{C_k, C_1}, \nu_{C_k, C_1} \rangle$	...	$\langle 1, 0 \rangle$	...	$\langle \mu_{C_k, C_n}, \nu_{C_k, C_n} \rangle$
...	...	...	...	...	...
C_n	$\langle \mu_{C_n, C_1}, \nu_{C_n, C_1} \rangle$	...	$\langle \mu_{C_n, C_k}, \nu_{C_n, C_k} \rangle$	...	$\langle 1, 0 \rangle$

The thresholds for μ_{C_k, C_l} and ν_{C_k, C_l} are determined algorithmically or are indicated by the user. Let $\alpha, \beta \in [0, 1]$ (with $\alpha > \beta$) be the thresholds values, then the pair of criteria C_k and C_l are said to be in:

- *positive consonance*, whenever $\mu_{C_k, C_l} > \alpha$ and $\nu_{C_k, C_l} < \beta$;
- *negative consonance*, whenever $\mu_{C_k, C_l} < \beta$ and $\nu_{C_k, C_l} > \alpha$;
- *dissonance*, otherwise.

Further clarifications on determining *consonance* or *dissonance* can be found in [122].

ICRA uses as an input a $m \times n$ table with the ratings of m objects (in particular, crude oil) against n criteria (in particular, physicochemical properties). As a result, ICRA

returns an $n \times n$ table of intuitionistic fuzzy pairs defining the IF-degrees of similarity and dissimilarity between each pair of criteria. ICRA evaluations can be performed using two free software packages, available as open-source software from <https://intercriteria.net/software/> (accessed on 18 June 2026) and described in detail in [135–137]. ICRA, applied to petroleum chemistry and processing data, performs pairwise comparisons between any two different physicochemical properties of all evaluated crude oils. μ -values and ν -values define the extent of the relationship between studied pairs. The values of μ and ν in the range $\mu = 0.95 \div 1.00$, $\nu = 0.00 \div 0.05$ denote a strong positive consonance, while values in the range $\mu = 0.85 \div 0.95$, $\nu = 0.05 \div 0.15$ imply an intermediate consonance. Dissonance is considered for the values of μ and ν where $\mu = 0.35 \div 0.65$, $\nu = 0.05 \div 0.15$ [138].

In order to define the values of μ and ν , which may be considered as quantitative indicators for assessing similarity, an ICRA analysis of all studied 1390 crude oils was performed. The geometric presentation of intuitionistic fuzzy evaluations obtained from ICRA [139,140] are presented as intuitionistic fuzzy interpretation triangle shown in Figure 8. It is evident from the data in Figure 9 that three types of relationships can be defined: dissonance, marked in red, intermediate/strong positive consonance, marked in blue and strong positive consonance marked in green. The characteristics of crude oils assigned in these three types of relationships are presented in Table 13. The data in Table 13 clearly show the significant difference between “Yolla” crude oil—which is an extra light crude oil/condensate—and the extra heavy crude oils “Gianna,” “Peace River bitumen,” and “Zuaata”. This distinction is very well reflected by ICRA, which classifies the pairs “Yolla-Gianna,” “Yolla-Peace River bitumen,” and “Yolla-Zuata” as dissonance, i.e., as completely different. The other crude oils—Arab Heavy, Arab Medium, Arab Light, Basrah Med, South Green Canyon, EBCO (Kirkuk), Urals, and Kuwait—which were processed in the refinery under study and whose pairs were marked in blue and green, are classified by ICRA as strong positive consonance and intermediate/strong consonance. These oils indeed demonstrated similar operational performance in the refinery under study. Based on this comparison, it can be inferred that crude oil pairs with $\mu \geq 0.95 \div 1.00$ and $\nu \leq 0.00 \div 0.05$ may be regarded as interchangeable, while those which exhibit $0.95 > \mu \geq 0.93$ and $0.07 \geq \nu > 0.05$ may be considered as very close to interchangeable.

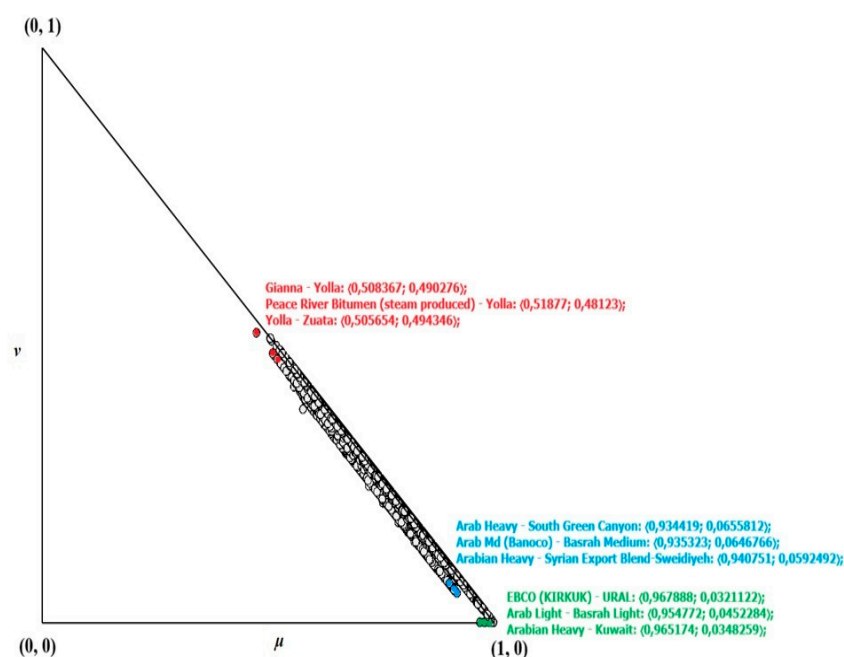


Figure 9. A geometric interpretation of intuitionistic fuzzy triangle.

Table 13. Characteristics of crude oils evaluated by ICrA as exemplified in Figure 9.

Origin	Italy	Australia	Canada	Venezuela	Saudi Arabia	Saudi Arabia	Iraq	Saudi Arabia	Iraq	Syria	Russia	Kuwait	USA
Crude Oil	Gianna	Yolla	Peace River Bitumen	Zuata	Arab Medium	Arab Heavy	Basra Med	Arab Light	EBCO (Kirkuk)	SS	Urals	Kuwait	South Green Canyon
Crude D15	1.015	0.759	1.012	1.005	0.872	0.889	0.878	0.858	0.8994	0.9211	0.877	0.873	0.883
Crude S, wt. %	9.00	0.01	5.54	3.35	2.48	2.91	2.85	1.89	3.54	4.08	1.53	2.67	2.26
Crude N, ppm	2770	16.70	4001	5550	1132	1635	1115	975	2400	1360	1907	1120	1570
Kw-characterizing factor	11.30	11.92	11.14	11.30	11.97	12.09	12.00	12.06	11.8	11.78	11.96	12.12	12.08
H-factor	1014.1	758.3	1010.9	1003.6	871.0	888.0	877.0	857.0	898.4	920.1	876.0	871.5	881.7
Pour point, °C	18.0	−16.0	10.0	24.0		−51.0	−30.0	−36.0	−15.4	−30.0	−9.0	−23.3	−35.6
TBP yields, wt. %													
Light naphtha (IBP–110 °C)	1.2	24.8	0.0	0.1	5.7	5.9	6.88	7.74	8.13	6	4.5	8.23	11.54
Heavy naphtha (110–180 °C)	3.1	34.7	0.3	0.5	9.9	8.8	9.78	11.68	10.28	8.29	10.2	10.12	8.97
Kerosene (180–240 °C)	3.8	10.9	3.2	2.5	9.9	7.6	8.92	9.84	8.35	7.62	9.2	8.40	6.00
Diesel (240–360 °C)	11.2	19.0	16.7	15.1	19.8	17.9	17.59	21.16	18.87	18.25	21.3	19.99	18.14
Vacuum gas oil (360–550 °C)	27.0	4.2	33.2	31.3	25.5	25.8	28.51	26.42	23.07	25.8	30.3	24.10	24.29
Vacuum residue (>550 °C)	53.3	0.0	46.7	50.5	27.9	32.5	25.87	21.26	30.30	33.04	23.0	28.16	30.06
Oil fraction density at 15 °C, g/cm ³													
Light naphtha (IBP–110 °C)	0.6678	0.6848		0.717	0.679	0.6745	0.678	0.675	0.6770	0.6817	0.7054	0.6949	0.7120
Heavy naphtha (110–180 °C)	0.7519	0.7837	0.8196	0.813	0.762	0.7551	0.750	0.758	0.7626	0.7602	0.7630	0.7639	0.7757
Kerosene (180–240 °C)	0.8187	0.8113	0.8522	0.858	0.804	0.7994	0.793	0.800	0.8023	0.8038	0.8093	0.8006	0.8132
Diesel (240–360 °C)	0.8993	0.8415	0.9162	0.915	0.854	0.8526	0.847	0.852	0.8632	0.8684	0.8553	0.8533	0.8625
Vacuum gas oil (360–550 °C)	0.9762	0.8258	0.9953	0.977	0.919	0.9333	0.933	0.927	0.9427	0.9486	0.9125	0.9214	0.9285
Vacuum residue (>550 °C)	1.1311		1.0807	1.065	1.039	1.0420	1.042	1.014	1.1056	1.1898	0.9934	1.0370	1.0500
Oil fraction sulfur content, wt. %													
Light naphtha (IBP–110 °C)	0.36	0.000		0.812	0.027	0.032	0.006	0.062	0.126	0.060	0.065	0.034	0.060
Heavy naphtha (110–180 °C)	0.87	0.001	1.010	0.432	0.055	0.078	0.056	0.081	0.182	0.188	0.103	0.078	0.136
Kerosene (180–240 °C)	3.06	0.007	1.950	0.606	0.271	0.277	0.280	0.214	0.343	0.496	0.255	0.272	0.336
Diesel (240–360 °C)	5.14	0.033	3.290	1.920	1.560	1.650	1.560	1.300	1.891	2.332	0.887	1.745	1.169
Vacuum gas oil (360–550 °C)	7.15	0.065	5.250	3.120	3.030	3.320	3.610	2.630	3.424	3.899	2.060	3.042	2.236
Vacuum residue (>550 °C)	11.30		7.620	4.360	5.560	5.610	6.160	4.340	7.216	7.107	2.950	5.652	5.089
Saturates, wt. %	21.1	86.3	18.5	20.3	52.2	45.0	49.2	54.8	43.7	38.3	54.85	50.9	47.5
Aromatics, wt. %	59.9	13.6	62.9	64.5	42.2	45.6	43.4	41.4	48.3	51.6	40.5	43.3	45.7
Resins, wt. %	6.5	0.1	7.0	5.3	3.4	5.1	4.6	2.6	4.5	5.6	3.4	3.4	3.2
Asphaltenes, wt. %	12.6	0.0	11.6	9.9	2.26	4.4	2.8	1.3	3.6	4.5	1.3	2.4	3.6

For $\mu < 0.93$ we still lack results to confirm that the behavior of crude oil pairs during refining is close enough to make a conservative evaluation regarding similarity in performance from the point of view of safety, environment protection, and reliable refining equipment operation.

3. Results and Discussion

3.1. Classification of the 1390 Crude Oils Using Different Classification Methods

Based on the values of K_W -characterizing factor, crude oils can be classified as paraffinic, mixed (paraffinic/naphthenic) and naphthenic/asphaltic as shown in Table 14 [6,141]. From the data in Figure 10, it can be seen that among the studied 1390 crude oils—which include crude oils characterized and processed in petroleum refineries worldwide for the last 50 years—paraffinic/naphthenic crude oils represent three-fourths of all studied crude oils. One-fourth are the paraffinic ones, and only 0.2% are naphthenic/asphaltic crude oils, having the lowest K_W -characterizing factor of 10.92 and the highest of 13.04 among the studied set. The highest BMCI is 83.7, while the lowest value is 2.0 for this data set.

Table 14. Classification of crude oil types based on the value of K_W -characterizing factor [6,141].

K_W -Characterizing Factor Range	Crude Oil Type	Characteristics	% of 1390 Crude Oils
>12.15	Paraffinic	High paraffin content	24.9%
11.0–12.0	Mixed	Paraffinic/naphthenic	74.9%
<11.0	Naphthenic/asphaltic		0.2%

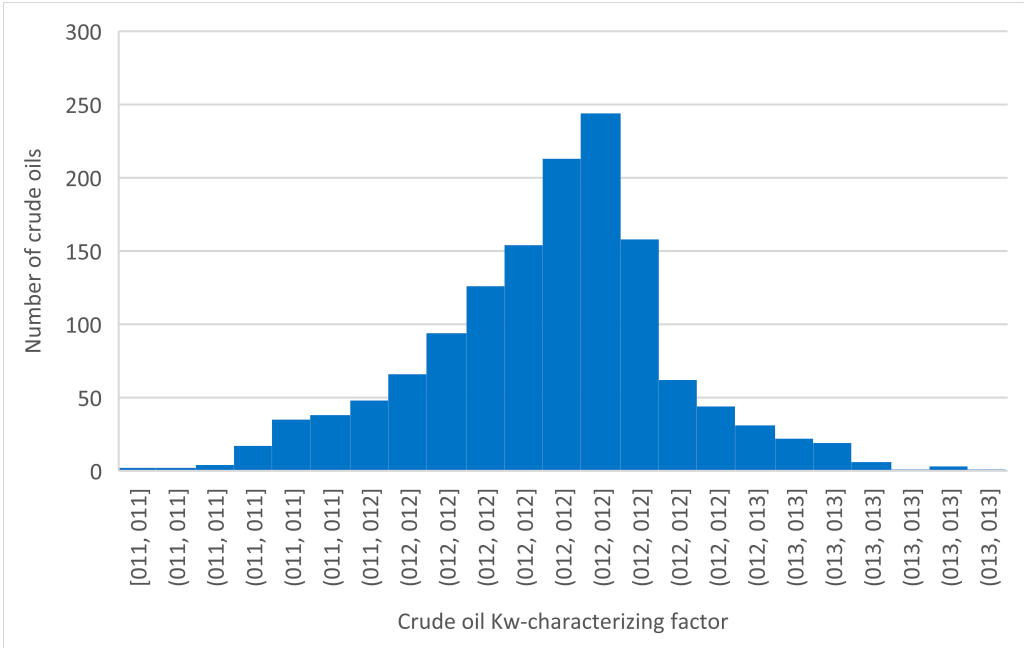
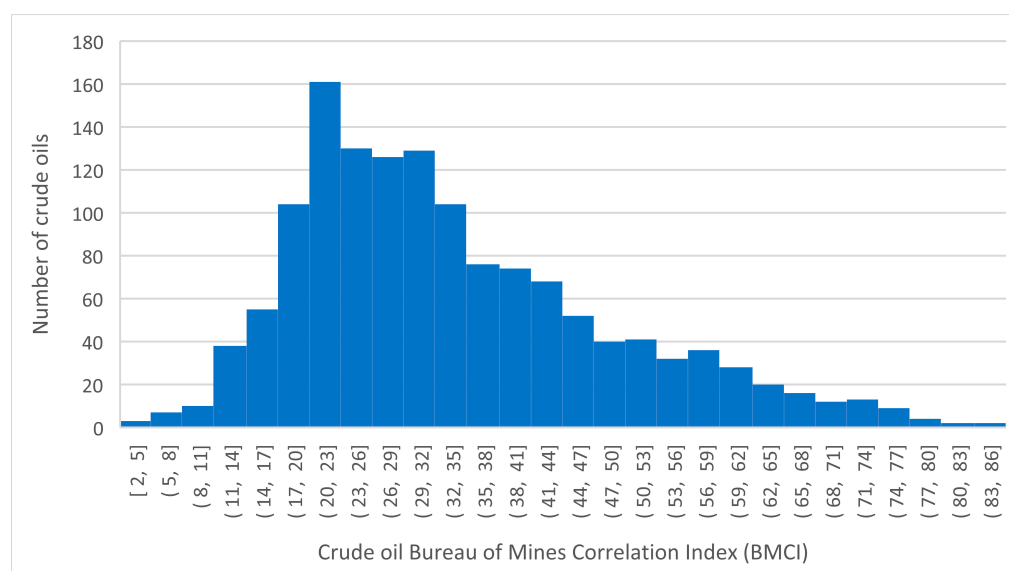


Figure 10. Histogram of K_W -characterizing factor of investigated 1390 crude oils.

Considering that crude oils are classified as paraffinic, mixed (paraffinic and aromatic), and aromatic [142,143] (see Table 15) the studied 1390 crude oils shown in Figure 11 are divided as indicated in Table 15: 5.3% paraffinic, 78.8% mixed, and 15.9% aromatic.

Table 15. Classification of crude oil types based on the value of *BMCI* [142,143] and their distribution across the studied 1390 crude oils.

<i>BMCI</i> Range	Crude Oil Type	Characteristics	% of 1390 Crude Oils
<15	Normal paraffinic	High paraffin content	5.3%
15–50.0	Mixed paraffinic and aromatic	Paraffinic–aromatic	78.8%
>50	Aromatic	High content of aromatic hydrocarbons	15.9%

**Figure 11.** Histogram of BMCI of investigated 1390 crude oils.

From the classification of crude oils based on their specific gravity—classified as extra light (or condensates), light, medium, heavy, and extra heavy [61] (see Table 16 and Figure 12)—it is observed that extra light crude oil are 7.3%, light crude oils are 34.5%, medium crude oils are 41.7%, heavy crude oils are 16.2%, and extra heavy crude oils are 0.3%.

Table 16. Classification of crude oil types based on their specific gravity [61] and distribution of crude oil types across the investigated 1390 crude oils.

Specific Gravity Range	Crude Oil Type	% of 1390 Crude Oils
<0.8017	Extra light	7.3%
0.8017–0.855	Light	34.5%
0.8600–0.9220	Medium	41.7%
>0.9220 <1.000	Heavy	16.2%
>1.000	Extra heavy	0.3%

The classification of crude oils based on saturate content, as shown in Table 5, categorizes crude oils into paraffinic, paraffinic–naphthenic and naphthenic when the saturate content is higher than 50 wt.%. When the saturate content is lower than 50 wt.%, then the crude oils are categorized as aromatic–intermediate, aromatic–naphthenic and aromatic–asphaltic. From the histogram of saturate content in the 1390 studied crude oils (Figure 13), it can be seen that 70.8% of the crude oils have saturate content higher than 50 wt.% and can therefore be assigned to the paraffinic, paraffinic–naphthenic and naphthenic groups. SARA analysis alone cannot separate this group into distinct subgroups, since SARA analysis cannot separate paraffins from naphthenes. It is interesting to note that the share

of paraffinic, paraffin–naphthenic, and naphthenic crude oils (Table 5) outweighs that of aromatic–intermediate, aromatic–naphthenic, and aromatic–asphaltic crude oils (62.5%), which corresponds to the trend observed in the data from Figure 13. This suggests that most refineries worldwide have processed mainly high saturate content crude oils during the past 50 years. Although it is reported that conventional crude oils, to which type the high saturate content crude oils belong, represent only 30% of global proven crude oil reserves [144], they have been the main feedstock for global oil refining for the past a half of century. The database used in this research embraces characterized crude oils processed in oil refineries worldwide; considering that most oil refineries were designed and constructed in the second half of previous century, one can understand why the proportion of lower saturate unconventional crude oils is so small.

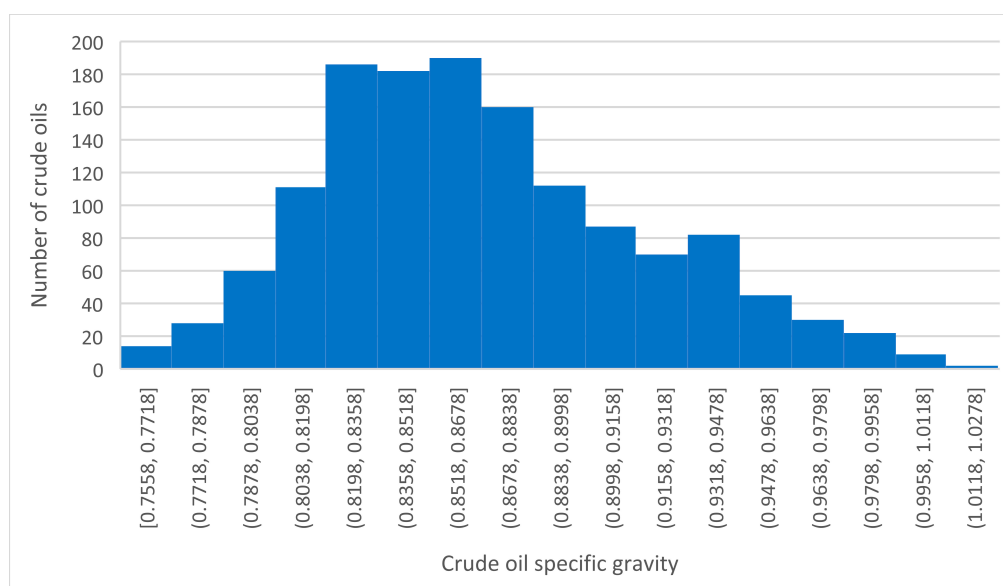


Figure 12. Histogram of specific gravity of investigated 1390 crude oils.

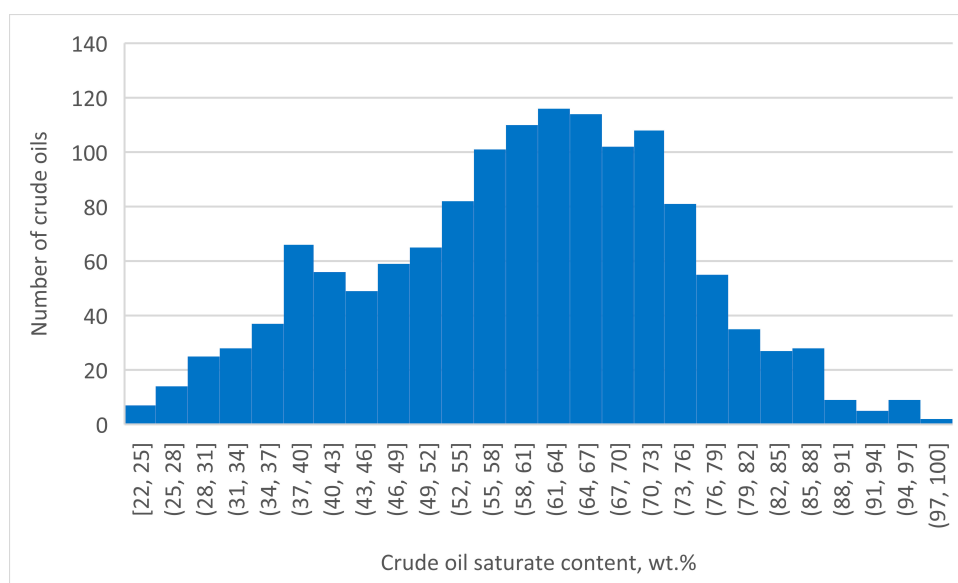


Figure 13. Histogram of saturate content in the investigated 1390 crude oils.

Figures S1–S4 show histograms of the sulfur, nitrogen, and asphaltene content, as well as the TAN, for the 1390 studied crude oils. The appearance of these histograms suggests

an exponential-like distribution, indicating that the components containing sulfur, nitrogen and acidic compounds correlate with the asphaltene content. In other words, the higher the asphaltene content in crude oil, the higher its sulfur and nitrogen content, and the more acidic the crude oil becomes. The classification of the studied 1390 crude oils according to their sulfur and nitrogen content, and acidity (TAN), is summarized in Table 17. The data in Table 17 indicate that the predominant share of investigated crude oils are low sulfur, low nitrogen nonacidic types.

Table 17. Classification of studied 1390 crude oils based on the content of sulfur, nitrogen and TAN.

Crude Oil Types Based on Sulfur Content	Low Sulfur (S < 0.5 wt.%)	Sulfur (1.5 wt.% > S > 0.5 wt.%)	High Sulfur (3.1 wt.% > S > 1.5 wt.%)	Extra High Sulfur (S > 3.1 wt.%)
Distribution among the 1390 studied crude oils	65%	13.4%	14.2%	7.4%
Crude Oil Types Based on Nitrogen Content	Nitrogen Poor (0.25 wt.% > Nitrogen)		Nitrogen Poor (0.25 wt.% ≥ Nitrogen)	
Distribution among the 1390 studied crude oils	80.4%		19.6%	
Crude Oil Types Based on Acidity (TAN)	Non-Acid (0.5 > TAN)	Acid (1.0 > TAN > 0.5)	High Acid (1.0 < TAN)	
Distribution among the 1390 studied crude oils	74.3%	10.2%	15.5%	

The classification of crude oils based on their oil precursor (the kerogen type) evaluated using the approach proposed by Barwise [105] and van den Berg [69,90] indicated the following distribution among studied 1390 crude oils studied: kerogen I type—24%; kerogen II type—69.5%; kerogen III type—1.5%; mixed kerogen type—5%. The data on the maturity of crude oils, estimated using the H-factor proposed by van den Berg et al. [69] and shown in Figure 14, indicate that 62% of the crude oils studied were mature, 20.4% were medium-mature, and 17.6% were immature.

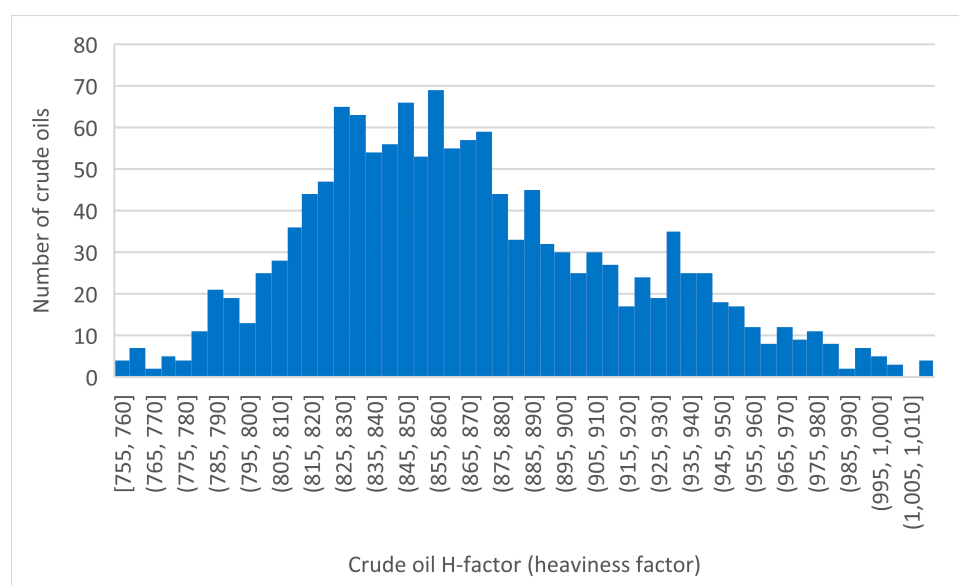


Figure 14. Histogram of H-factor (heaviness factor ~ maturity) in the investigated 1390 crude oils.

The classification of crude oils based on the density of the key fractions shown in Table 4, applied to the 1390 crude oils studied, exhibited the following distribution: intermediate/intermediate—60.8%; naphthenic/naphthenic—19.6%; intermediate/paraffinic—11.8%; intermediate/naphthenic—7.8%.

All examined classifications suggest different categorization of studied crude oils and their meaning for the crude selection process will be assessed in the next subsection.

3.2. Proposed New Crude Oil Classification Based on Refinery Performance, Crude Oil Properties and ICrA Evaluation

Table 18 summarizes the properties of the crude oils processed at the refinery under study, as well as the various classifications of crude oils, including an assessment of the performance characteristics of the processed crude oils. These data show that the oil refinery did not process all existing types of crude oils, but this table focuses on those crude oils that caused problems during processing, as discussed in Section 2.4. Irrespective of the various classifications of crude oils listed in Table 18, eight crude oils out of 11 demonstrated operational problems during their refining. As evident from the data in Table 17 the problematic crude oils are classified as kerogen I and II, and mixed I/II types, mature and medium, intermediate/intermediate, naphthenic/naphthenic, medium and heavy. It is worth noting here that no correlation was found between any classification and the operational results, implying that refiners should rely on something more than the available classifications during the process of crude oil selection. For this reason, we decided to classify crude oils based on their similarity to those that showed good, medium and poor results, using comprehensive crude oil assay data and ICrA assessments. In this way, crude oils that show a high degree of similarity to those that demonstrated behavior that could be classified as harmful to refinery equipment can be excluded from the list of feedstocks for the refinery. In contrast, crude oils showing a high degree of similarity to those with good performance may be accepted for refining once the economic attractiveness of their processing has been proven.

Table 19 presents a summary of the ICrA evaluation of crude oils from Table 18 against the comprehensive assay data of the 1390 studied crude oils. It can be seen that some of the crude oils from Table 16 exhibit a very strong consonance ($\mu > 0.95$; $\nu < 0.05$) with some of the crude oils from the examined database of 1390 crude oils such as crude oils BSP, BTV, BM, NSJ, PG. This may suggest that those crude oils having $\mu > 0.95$; $\nu < 0.05$ would display similar performance as that of the mentioned crude oils in the studied petroleum refinery. Actually, ICrA evaluation of crude oils has already been employed in the examined petroleum refinery to select crude oils and demonstrated a good substitution of crude oils having ICrA $\mu > 0.95$; $\nu < 0.05$. The data in Table 19, however, show that crude oils such as CV, CC, and MM do not indicate μ higher than 0.92 and ν lower than 0.08 with any of oil from the examined database of 1390 studied oils. This may imply that these crude oils cannot be completely interchangeable with any of the crude oils from the studied crude oil database from 1390 crude oils. Nevertheless, these ICrA assessments warn that crude oils that show moderate to strong consonance with the CV, CC, and MM crude oils and have $\mu \geq 0.91$; $\nu \leq 0.09$, may exhibit similar adverse operational characteristics during their processing at the refinery under study, and for this reason it would be more prudent to refrain from refining them.

Table 18. Characteristics of crude oils processed in the studied refinery along with crude oil classification.

Crude Oil	LEB	TR	CV	CC	EO	MM	BSP	BTV	BM	NJS	PG
Crude density at 15 °C, g/cm ³	0.891	0.865	0.9189	0.939	0.9095	0.923	0.8883	0.893	0.8783	0.8867	0.8849
Crude sulfur, wt.%	1.76	0.75	1.06	1.811	1.59	3.4	0.41	0.73	0.32	0.804	0.69
Crude nitrogen, ppm	1876	1611	2032	2619	1757	3414	3820	3560	3220	2157	2030
K _W -characterizing factor	11.95	11.93	11.70	11.64	11.48	11.89	12.17	12.0	12.14	11.91	11.84
H-factor	890.0	864.0	917.9	938.0	908.5	922.0	887.3	892.0	877.3	885.7	883.9
Pour point, °C	0.0	−18.0	−36.0	−24.0	−9.0	−17.8	9.0	−39.0	−21.0	−22.0	−1.0
TBP yields, wt.%											
Light naphtha (IBP–110 °C)	6.4	10.4	8.11	6.2	3.2	5.3	8.11	8.55	7.93	8.41	7.7
Heavy naphtha (110–180 °C)	8.9	12.6	8.04	4.1	6.0	8.5	8.04	8.01	9.01	7.98	8.98
Kerosene (180–240 °C)	8.2	9.2	7.39	3.5	5.9	7.7	7.39	7.51	8.17	8.29	8.63
Diesel (240–360 °C)	18.8	21.6	17.46	17.3	15.3	17.1	17.46	18.89	19.27	23.34	24.31
Vacuum gas oil (360–550 °C)	32.4	27.4	29.49	29.6	28.3	24.8	29.49	29.83	29.94	29.46	31.0
Vacuum residue (>550 °C)	25.4	18.8	29.51	37.7	40.6	35.3	29.51	27.21	25.68	22.52	18.4
Oil fraction density at 15 °C, g/cm ³											
Light naphtha (IBP–110 °C)	0.7092	0.7240	0.6954	0.676	0.710	0.6824	0.695	0.6993	0.694	0.6910	0.697
Heavy naphtha (110–180 °C)	0.7740	0.7772	0.7688	0.791	0.769	0.7596	0.769	0.7725	0.767	0.7766	0.773
Kerosene (180–240 °C)	0.8170	0.8168	0.8151	0.854	0.819	0.8122	0.815	0.8191	0.778	0.8251	0.820
Diesel (240–360 °C)	0.8611	0.8535	0.8596	0.897	0.869	0.8689	0.860	0.8651	0.857	0.8758	0.868
Vacuum gas oil (360–550 °C)	0.9108	0.9109	0.9224	0.964	0.934	0.9434	0.922	0.9305	0.921	0.9231	0.922
Vacuum residue (>550 °C)	1.0397	1.0062	0.9984	1.083	1.058	1.0837	0.998	1.0081	0.984	1.0266	1.001
Oil fraction sulfur content, wt.%											
Light naphtha (IBP–110 °C)	0.05	0.049	0.036	0.011	0.023	0.061	0.036	0.019	0.0265	0.026	0.035
Heavy naphtha (110–180 °C)	0.04	0.056	0.069	0.037	0.066	0.161	0.069	0.106	0.0580	0.034	0.044
Kerosene (180–240 °C)	0.17	0.101	0.093	0.150	0.216	0.766	0.093	0.227	0.0792	0.084	0.090
Diesel (240–360 °C)	1.24	0.524	0.219	0.665	1.150	2.040	0.219	0.529	0.1821	0.495	0.340
Vacuum gas oil (360–550 °C)	1.91	0.980	0.410	1.580	2.020	3.020	0.410	0.800	0.3551	0.928	0.709
Vacuum residue (>550 °C)	3.37	1.895	0.754	2.930	2.980	5.060	0.754	1.354	0.6340	1.775	1.354
Saturates, wt.%	49.5	56.3	41.6	39.5	38.0	32.1	51.5	50.1	54.7	44.5	38.5
Aromatics, wt.%	43.9	38.6	43.9	43.8	48.8	53.3	44.0	45.1	43.3	50.6	59.5
Resins, wt.%	3.5	3.0	5.3	6.6	5.6	6.8	3.3	2.9	1.6	2.9	1.3
Asphaltenes, wt.%	3.1	2.2	6.8	10.0	7.6	7.8	1.2	1.9	0.4	2.0	0.7
Classification based on K _W -characterizing factor	mixed	mixed	mixed	mixed	mixed	mixed	paraffinic	mixed	mixed	mixed	mixed
Classification based on the key fraction 250–300 °C	intermediate	intermediate	naphthenic	naphthenic	intermediate	intermediate	intermediate	intermediate	intermediate	naphthenic	intermediate
Classification based on the key fraction 389–415 °C	intermediate	intermediate	intermediate	naphthenic	intermediate	intermediate	intermediate	intermediate	intermediate	intermediate	intermediate
Classification based on Kerogen type	Kerogen I/II	Kerogen I	Kerogen II	Kerogen II	Kerogen II	Kerogen II	Kerogen I	Kerogen I	Kerogen I	Kerogen II	Kerogen I
Classification based on maturity	medium	mature	medium	medium	medium	medium	medium	medium	mature	medium	medium
Classification based on specific gravity	medium	medium	medium	heavy	medium	heavy	medium	medium	medium	medium	medium

Table 18. Cont.

Crude Oil	LEB	TR	CV	CC	EO	MM	BSP	BTV	BM	NJS	PG
Classification based on the presence of operational issues of studied refinery	Poor (high sedimentation rate in H-Oil and reactor fluidized bed instability)	Poor (high sedimentation rate in H-Oil)	Poor (high sedimentation rate in H-Oil and reactor fluidized bed instability)	Poor (high sedimentation rate in H-Oil and reactor fluidized bed instability)	Poor (high sedimentation rate in H-Oil and reactor fluidized bed instability)	Poor (Very high acidity in CDU sour water)	Poor (Very high acidity in CDU sour water; exceptionally high fouling rate in H-Oil)	Poor (Very high acidity in CDU sour water; exceptionally high fouling rate in H-Oil)	Poor (Very high acidity in CDU sour water)	Medium (Exceptionally high fouling rate in H-Oil when blended with BSP and BTV; no operational issues when blended with Basrah Heavy)	Good (No operational issues)

Table 19. Crude oils from the database of 1390 crude oils exhibiting the closest similarity with the crude oils from Table 16.

LEB	TR	CV	CC	EO	MM	BSP	BTV	BM	NJS	PG
Claymore (UK) $\mu = 0.95$; $\nu = 0.05$	Unity Gold (Guyana) $\mu = 0.96$; $\nu = 0.04$	Canagney (Colombia) $\mu = 0.91$; $\nu = 0.09$	Apiay Blend (Colombia) $\mu = 0.92$; $\nu = 0.08$	Cohembi (Colombia) $\mu = 0.94$; $\nu = 0.06$	Bashkiri Heavy (Russia) $\mu = 0.92$; $\nu = 0.08$	Buzios (Brazil) $\mu = 0.96$; $\nu = 0.04$	Roncador (Brazil) $\mu = 0.95$; $\nu = 0.05$	Lula (Brazil) $\mu = 0.97$; $\nu = 0.03$	Grane (Norway) $\mu = 0.96$; $\nu = 0.04$	Hungo (Angola) $\mu = 0.96$; $\nu = 0.04$
South Blend (Colombia) $\mu = 0.95$; $\nu = 0.05$	Cyrus (UK) $\mu = 0.95$; $\nu = 0.05$	South Blend (Colombia) $\mu = 0.91$; $\nu = 0.09$	Llanos Blend Heavy (Colombia) $\mu = 0.91$; $\nu = 0.09$		Cecil (Canada) $\mu = 0.91$; $\nu = 0.09$	Baleias (Brazil) $\mu = 0.95$; $\nu = 0.05$	Sururu (Brazil) $\mu = 0.95$; $\nu = 0.05$	Sapinhua Crude (Brazil) $\mu = 0.96$; $\nu = 0.04$	Furrial (Venezuela) $\mu = 0.95$; $\nu = 0.05$	Kissanje (Angola) $\mu = 0.96$; $\nu = 0.04$
Poseidon (USA) $\mu = 0.95$; $\nu = 0.05$	South Blend (Colombia) $\mu = 0.95$; $\nu = 0.05$	Chaza (Colombia) $\mu = 0.91$; $\nu = 0.09$	Frontera Heavy (Colombia) $\mu = 0.91$; $\nu = 0.09$		Zaafarana (Egypt) $\mu = 0.91$; $\nu = 0.09$	Tartaruga Verde (Brazil) $\mu = 0.94$; $\nu = 0.06$	Iara Crude (Brazil) $\mu = 0.95$; $\nu = 0.05$	Iara Crude (Brazil) $\mu = 0.96$; $\nu = 0.04$	Baleias (Brazil) $\mu = 0.95$; $\nu = 0.05$	Mostarda (Angola) $\mu = 0.95$; $\nu = 0.05$
WEST DON (UK) $\mu = 0.94$; $\nu = 0.06$	Gindungo (Angola) $\mu = 0.95$; $\nu = 0.05$	Caripito Blend 24 (Venezuela) $\mu = 0.91$; $\nu = 0.09$	Pozo Tua (Colombia) $\mu = 0.91$; $\nu = 0.09$		Syrian Export Blend-Sweidiyeh (Syria) $\mu = 0.91$; $\nu = 0.09$	Iara Crude (Brazil) $\mu = 0.94$; $\nu = 0.06$	Baleias (Brazil) $\mu = 0.95$; $\nu = 0.05$	Buzios (Brazil) $\mu = 0.96$; $\nu = 0.04$	South Blend (Colombia) $\mu = 0.95$; $\nu = 0.05$	Djeno (Congo) $\mu = 0.95$; $\nu = 0.05$
Orito (Colombia) $\mu = 0.94$; $\nu = 0.06$	Masila (Yemen) $\mu = 0.95$; $\nu = 0.05$		Mares Blend (Colombia) $\mu = 0.91$; $\nu = 0.09$		Cascade (USA) $\mu = 0.91$; $\nu = 0.09$	LAPA (Brazil) $\mu = 0.94$; $\nu = 0.06$	Lula (Brazil) $\mu = 0.95$; $\nu = 0.05$	Atapu (Brazil) $\mu = 0.96$; $\nu = 0.04$	Linguado Crude (Brazil) $\mu = 0.94$; $\nu = 0.06$	Saldahna Heavy (South Africa) $\mu = 0.95$; $\nu = 0.05$
Rhemoura (Tunisia); $\mu = 0.94$; $\nu = 0.06$	WEST DON (UK) $\mu = 0.94$; $\nu = 0.06$		Guadalupe (Colombia) $\mu = 0.91$; $\nu = 0.09$		Ras Gharib (Egypt) $\mu = 0.91$; $\nu = 0.09$	Linguado Crude (Brazil) $\mu = 0.94$; $\nu = 0.06$	SEPIA (Brazil) $\mu = 0.94$; $\nu = 0.06$	Sururu (Brazil) $\mu = 0.96$; $\nu = 0.04$	Poseidon (USA) $\mu = 0.94$; $\nu = 0.05$	Liza (Guyana) $\mu = 0.95$; $\nu = 0.05$

The μ -value of 0.94 and the ν -value of 0.06 observed for BSP and BTV crude oils, as well as for LEB and TRR crude oils, which showed poor results, suggest that the range of interchangeability can be extended to include the values of $\mu = 0.94$ and $\nu = 0.06$, i.e., the full range of interchangeability can be considered for the range $\mu \geq 0.94$ and $\nu \leq 0.06$.

The ICRA approach demonstrates the ability to distinguish between suitable and unsuitable crude oils and those that are in between, and can be classified as appropriate or inappropriate depending on the other crude oils in the processed crude oil blend. For example, NSJ crude oil showed poor performance when processed together with BS and BTV [74], but when refined with Basra Heavy, it showed very good performance.

According to the theory of ICRA [145] the presence of strong consonance quantified by the fuzzy pairs $\mu > 0.95$; $\nu < 0.05$ implies very high extent of similarity. The range of fuzzy pairs $0.95 > \mu > 0.85$ and $0.15 > \nu > 0.05$ implies medium consonance and intermediate extent of similarity of examined crude oils. However, the medium consonance has relatively wide diapason of the fuzzy pair μ and ν variation. One can deem that the strong consonance is equivalent to interchangeability between crude oils, while the values of μ and ν which are very close to the strong consonance with μ - and ν -values in the range $0.95 > \mu > 0.90$ probably may be attributed to the crude oils which have relatively high extent of similarity. In order to determine which values of μ and ν can be considered as indicative for the classification of a given crude oil candidate as suitable or unsuitable for processing in the refinery under study, we summarized the performance of 24 crude oils classified as suitable (good performers) and four crude oils classified as unsuitable (poor performers), along with their calculated by ICRA μ and ν -values in Table 20. The assumption of interchangeability for the crude oils with strong consonance $\mu \geq 0.95$ and $\nu \leq 0.05$ was confirmed with the 24 crude oils exhibiting good performance as shown in Table 20.

Table 20. Summary of ICRA evaluation for 24 crude oils exhibiting good performance and four crude oils demonstrating poor performance.

Crude Oils	Performance	Classified by ICRA Counterparts of Crude Oils with the Same Performance		
Arabian Heavy	Good performer	Kuwait ($\mu = 0.96$; $\nu = 0.04$) (good performer)	Basrah ($\mu = 0.96$; $\nu = 0.04$) (good performer)	Basrah Med ($\mu = 0.96$; $\nu = 0.04$) (good performer)
Arab Light	Good performer	Basrah Light ($\mu = 0.95$; $\nu = 0.05$) (good performer)		
Basrah Medium	Good performer	Kuwait ($\mu = 0.95$; $\nu = 0.05$) (good performer)		
Siberian Light	Good performer	Es Sider ($\mu = 0.95$; $\nu = 0.05$) (good performer)	Bryan Mound ($\mu = 0.95$; $\nu = 0.05$) (good performer)	Gulf of Suez ($\mu = 0.95$; $\nu = 0.05$) (good performer)
Azeri Light	Good performer	Cheleken ($\mu = 0.96$; $\nu = 0.04$) (good performer)		
Gulf Of Suez	Good performer	Siberian Light ($\mu = 0.95$; $\nu = 0.05$) (good performer)		
Es Sider	Good performer	Sirtica ($\mu = 0.96$; $\nu = 0.04$) (good performer)		
Bryan Mound Sour	Good performer	Arab Light ($\mu = 0.95$; $\nu = 0.05$) (good performer)		
Souedie	Good performer	Kirkuk Heavy ($\mu = 0.96$; $\nu = 0.04$) (good performer)		
Arab Medium	Good performer	Arab Heavy ($\mu = 0.96$; $\nu = 0.04$) (good performer)	Kuwait ($\mu = 0.96$; $\nu = 0.04$) (good performer)	Basrah ($\mu = 0.96$; $\nu = 0.04$) (good performer)
Kirkuk Heavy	Good performer	Basrah Heavy ($\mu = 0.95$; $\nu = 0.05$) (good performer)		
BSP	Poor performer	BTB ($\mu = 0.94$; $\nu = 0.06$) (poor performer)		
LEB	Poor performer	TR ($\mu = 0.94$; $\nu = 0.06$) (poor performer)		

The data in Table 20 suggest that a conservative approach to the selection of appropriate crude oil or reject the inappropriate crude oils for processing in the refinery under study can be based on the presence of strong consonance ($\mu \geq 0.94$; $\nu \leq 0.06$). Additional

investigations are needed to prove that the threshold values for μ and ν may be relaxed slightly, which can widen the selection range used in the process of crude selection. Further refinement of this approach is underway and the definition of the most informative properties of crude oil is being explored to reduce the cost of crude oil characterization.

Another interesting observation from the results of the ICRA assessment of the 1390 crude oils is that no perfect match ($\mu = 1.00$; $\nu = 0.00$) was found between any of the crude oils studied, showing a maximum μ of 0.97 and a minimum ν of 0.03. This confirms the statement that no two crude oils are identical [146].

4. Conclusions

Thirty-one classifications of crude oils have been reviewed in this work, and some of them were applied to a database of comprehensive assays for 1390 crude oils. The examined crude oils are categorized as paraffinic, mixed, naphthenic/asphaltic, aromatic, extra light, light, medium, heavy, extra heavy, nonacidic, acidic, high acidic, kerogen I, kerogen II, kerogen III, mature, immature, nitrogen poor, nitrogen-rich, and others. Unfortunately, these classifications are not sufficient to distinguish crude oils that tend to cause operational problems and threaten safety and environmental protection during their processing in a refinery with a specific process flow. None of the classification methods studied proved useful regarding the relationship between crude oil classification and its performance in the studied oil refinery. The application of ICRA has shown that crude oils classified as good, medium, and poor can be assessed against other crude oils based on comprehensive assay data and that the extent of similarity can be quantified. Crude oils that exhibit strong positive consonance ($\mu > 0.95$; $\nu < 0.05$) with the crude oils whose performance is known could be considered interchangeable and can be accepted or rejected for processing depending on the performance of their counterparts. This strong positive consonance, expressed by the intuitionistic fuzzy pairs ($\mu > 0.95$; $\nu < 0.05$), serves as the quantitative criterion for similarity between a new potential crude oil candidate for processing and another crude oil already processed in the refinery under study.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/pr14132159/s1>, Figure S1: Histogram of sulfur content of studied 1390 crude oils; Figure S2: Histogram of nitrogen content of studied 1390 crude oils; Figure S3: Histogram of asphaltene content of studied 1390 crude oils; Figure S4: Histogram of TAN of studied 1390 crude oils.

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Abbreviations

The following abbreviations are used in this manuscript:

AA	Aromatic content, wt. %
ACN	Average carbon number
API	American Petroleum Institute
Asp	Asphaltenes, wt. %
ASTM	American Society for Testing and Materials
ATR-FTIR	Attenuated Total Reflectance Fourier transform infrared spectroscopy
BMC	Bureau of Mines Correlation Index
CCR	Conradson carbon content, wt. %
CDU	Crude oil distillation unit
COW	Correlation optimized warping
ED	Euclidean distance
EWHC	EWard's hierarchical clustering
FCC	Fluid catalytic cracking
FTIR	Fourier transform infrared
GC	Gas chromatography
HCA	Hierarchical cluster analysis hierarchical clustering
HDS	Hydrodesulphurization unit
ICrA	Intercriteria analysis
IF	Intuitionistic fuzzy pair
IR	Infrared
LDA	Linear Discriminant Analysis
LPG	Liquefied petroleum gas
MIR	Mid-infrared spectroscopy
MMWCC	Modified moving window correlation coefficient
μTADs	Microfluidic thread-based analytical devices
N	Nitrogen content, wt. %
Naph	Naphthenes, wt. %
NIR	Near-infrared spectroscopy
NMR	Nuclear Magnetic Resonance
P	Paraffins
PCA	Principal Component Analysis
PIANO	Paraffins, Iso-paraffins, Aromatics, Naphthenes, Olefins
PLS	Partial Least Squares
PLS-DA	Partial Least Squares Discriminant Analysis
PLS-R	Partial Least Squares Regression
Ph	Phytane
Pr	Pristane
¹ H-NMR	Proton nuclear magnetic resonance
S	Sulfur content, wt. %
Sat	Saturates, wt. %
SG	Specific gravity
SIMCA	Soft Independent Modeling of Class Analogy
SVM-R	Support Vector Machine Regression
TAN	Total acid number
TBP	True Boiling point
t-SNE	t-distributed stochastic neighbor embedding
UMAP	Uniform manifold approximation and projection
UV-Vis	Ultraviolet-visible
UHRMS	Ultra-high-resolution mass spectrometry
VIS	Viscosity

References

- Jing, L.; El-Houjeiri, H.M.; Monfort, J.C.; Brandt, A.R.; Masnadi, M.S.; Gordon, D.; Bergerson, J.A. Carbon Intensity of Global Crude Oil Refining and Mitigation Potential. *Nat. Clim. Change* **2020**, *10*, 526–532. [CrossRef]
- World Energy Outlook 2025. International Energy Agency. Available online: <https://iea.blob.core.windows.net/assets/9753df19-0a71-422a-b725-012c555763b3/WorldEnergyOutlook2025.pdf> (accessed on 13 May 2026).
- Demand for Crude Oil Worldwide from 2005 to 2025, with a Forecast for 2026. Available online: <https://www.statista.com/statistics/271823/global-crude-oil-demand/> (accessed on 13 May 2026).
- Zhang, Y. Perspectives on a New Age of Materials for Petroleum. *Energy Fuels* **2022**, *36*, 5529–5530. [CrossRef]
- Broeke, T. PAC Core GC Portfolio. In Proceedings of the IV ROFA symposium, Belgrade, Serbia, 7–9 May 2025.
- Speight, J.G. *The Chemistry and Technology of Petroleum*, 5th ed.; CRC Press: Boca Raton, Florida, USA, 2014.
- Ramirez-Corredores, M.M. *The Science and Technology of Unconventional Oils: Finding Refining Opportunities*; Elsevier: Cambridge, MA, USA, 2017.
- Altgelt, K.H. *Composition and Analysis of Heavy Petroleum Fractions*, 1st ed.; CRC Press: Boca Raton, USA, 2016.
- Ovalles, C.; Moir, M.E.; Rogel, E.; Morazan, H.; Roye, M.; Vien, J.; Witt, M.; Pradhan, A.; Boduszynski, M.M.; Leong, D.; et al. *The Boduszynski Continuum: Contributions to the Understanding of the Molecular Composition of Petroleum*; ACS Symposium Series; American Chemical Society (ACS): Washington, DC, USA, 2018; Volume 1282.
- Schobert, H. Chapter 11 Composition, Classification, and Properties of Petroleum. In *Chemistry of Fossil Fuels and Biofuels*; Cambridge University Press: Cambridge, UK, 2013.
- Zhou, X.; Shi, Q.; Zhang, Y.; Zhao, S.; Zhang, R.; Chung, K.H.; Xu, C. Analysis of Saturated Hydrocarbons by Redox Reaction with Negative-Ion Electrospray Fourier Transform Ion Cyclotron Resonance Mass Spectrometry. *Anal. Chem.* **2012**, *84*, 3192–3199. [CrossRef] [PubMed]
- Schuler, B.; Fatayer, S.; Meyer, G.; Rogel, E.; Moir, M.; Zhang, Y.; Harper, M.R.; Pomerantz, A.E.; Bake, K.D.; Witt, M.; et al. Heavy Oil Based Mixtures of Different Origins and Treatments Studied by Atomic Force Microscopy. *Energy Fuels* **2017**, *31*, 6856–6861. [CrossRef]
- Chacón-Patiño, M.L.; Smith, D.F.; Hendrickson, C.L.; Marshall, A.G.; Rodgers, R.P. Advances in Asphaltene Petroleomics. Part 4. Compositional Trends of Solubility Subfractions Reveal That Polyfunctional Oxygen-Containing Compounds Drive Asphaltene Chemistry. *Energy Fuels* **2020**, *34*, 3013–3030. [CrossRef]
- Petroleum Refining and Insurance Part I. Crude Oil Refining—A Constantly Evolving Industry. Available online: https://www.scor.com/sites/default/files/pc_nl_raffinage_i.pdf (accessed on 5 December 2025).
- Kaiser, M.J.; de Klerk, A.; Gary, J.H.; Handwerk, G.E. *Petroleum Refining: Technology, Economics, and Markets*, 6th ed.; CRC Press: Boca Raton, FL, USA, 2019.
- Swafford, P.; McCarthy, R. Improving Crude Oil Selection. *PTQ Mag.* **2008**, *3*, 125–129. Available online: https://scholar.google.com/scholar_lookup?title=Improving+crude+oil+selection&author=Swafford,+P.&author=McCarthy,+R.&publication_year=2008&journal=PTQ+Mag.&volume=3&pages=125%E2%80%93129 (accessed on 11 June 2026).
- Zavarce, A. Crude Oil Classification: Types and Key Properties. 2024. Available online: <https://inspenet.com/en/articulo/types-of-crude-oil-classification/> (accessed on 11 December 2025).
- Moro, M.K.; de Castro, E.V.R.; Romão, W.; Filgueiras, P.R. Data Fusion Applied in near and Mid Infrared Spectroscopy for Crude Oil Classification. *Fuel* **2023**, *340*, 127580. [CrossRef]
- Garmarudi, A.B.; Khanmohammadi, M.; Fard, H.G.; de la Guardia, M. Origin Based Classification of Crude Oils by Infrared Spectrometry and Chemometrics. *Fuel* **2019**, *236*, 1093–1099. [CrossRef]
- Mohammadi, M.; Khorrami, M.K.; Vatani, A.; Ghasemzadeh, H.; Vatanparast, H.; Bahramian, A.; Fallah, A. Rapid Determination and Classification of Crude Oils by ATR-FTIR Spectroscopy and Chemometric Methods. *Spectrochim. Acta A Mol. Biomol. Spectrosc.* **2020**, *232*, 118157. [CrossRef] [PubMed]
- GOST P 51858-2020; Crude Petroleum. General Specifications. Standartinform: Moscow, Russia, 2020.
- Behrenbruch, P.; Dedigama, T. Classification and Characterisation of Crude Oils Based on Distillation Properties. *J. Pet. Sci. Eng.* **2007**, *57*, 166–180. [CrossRef]
- Zhou, J.; Huang, Z.; Shi, Y.; Chen, X.; Song, C.; Ma, X.; Zhan, H.; Guo, W. Machine Learning-Assisted Rapid Screening of Oil Types on Microfluidic Thread-Based Analytical Devices (MTADs). *Anal. Chim. Acta* **2026**, *1383*, 344899. [CrossRef] [PubMed]
- de Peinder, P. Characterization and Classification of Crude Oils Using a Combination of Spectroscopy and Chemometrics. Ph.D. Thesis, Utrecht University, Utrecht, The Netherlands, 2009.
- Tissot, B.P.; Welte, D.H. *Petroleum Formation and Occurrence*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 1984.
- Niyonsaba, E.; Wehde, K.E.; Yerabolu, R.; Kilaz, G.; Kenttämaa, H.I. Determination of the Chemical Compositions of Heavy, Medium, and Light Crude Oils by Using the Distillation, Precipitation, Fractionation Mass Spectrometry (DPF MS) Method. *Fuel* **2019**, *255*, 115852. [CrossRef]

27. Speight, J.G. Chapter 1—Occurrence and Formation of Natural Gas and Crude Oil. In *Handbook of Offshore Oil and Gas Operations*; Gulf Professional Publishing: Houston, TX, USA, 2011; pp. 1–43.
28. Kornienko, V.; Avtonomov, P. Application of Neutron Activation Analysis for Heavy Oil Production Control. *Procedia Soc. Behav. Sci.* **2015**, *195*, 2451–2456. [\[CrossRef\]](#)
29. Heavy Oil vs. Light Oil. Available online: https://tc.canada.ca/sites/default/files/migrated/hres_3_10_11_lunch_learn_bp_heavy_oil1.pdf (accessed on 10 December 2025).
30. Manfroni, M.; Bukkens, S.G.F.; Giampietro, M. Securing Fuel Demand with Unconventional Oils: A Metabolic Perspective. *Energy* **2022**, *261*, 125256. [\[CrossRef\]](#)
31. Ma, G.; Jia, J.; Qi, Z.; Peng, S. Unconventional Oil Ores around the World: A Review. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *621*, 012009. [\[CrossRef\]](#)
32. Zhang, L.; Lai, F.; Xu, X.; Zhang, X. Evaluation of Recoverable Reserves Based on Dynamic Data for Horizontal Wells in Unconventional Oil Reservoir. *Geoenergy Sci. Eng.* **2025**, *244*, 213493. [\[CrossRef\]](#)
33. What Is “Unconventional” Oil and Gas? Available online: <https://www.planete-energies.com/en/media/article/what-unconventional-oil-and-gas> (accessed on 10 December 2025).
34. Mayer, A. Quality of Life and Unconventional Oil and Gas Development: Towards a Comprehensive Impact Model for Host Communities. *Extr. Ind. Soc.* **2017**, *4*, 923–930. [\[CrossRef\]](#)
35. Castro-Alvarez, F.; Marsters, P.; Ponce de León Barido, D.; Kammen, D.M. Sustainability Lessons from Shale Development in the United States for Mexico and Other Emerging Unconventional Oil and Gas Developers. *Renew. Sustain. Energy Rev.* **2018**, *82*, 1320–1332. [\[CrossRef\]](#)
36. Liu, S. Review of the Development Status and Technology of Tight Oil: Advances and Outlook. *Energy Fuels* **2023**, *37*, 14645–14665. [\[CrossRef\]](#)
37. Zhang, X.S.; Wang, H.J.; Ma, F.; Sun, X.C.; Zhang, Y.; Song, Z.H. Classification and Characteristics of Tight Oil Plays. *Pet. Sci.* **2016**, *13*, 18–33. [\[CrossRef\]](#)
38. Benoit, B.; Zurlo, J. Overcoming the Challenges of Tight/Shale Oil Refining. Processing Shale Feedstocks. 2014. Available online: <https://www.digitalrefining.com/article/1000979/overcoming-the-challenges-of-tight-shale-oil-refining> (accessed on 11 December 2025).
39. Jia, C.; Zou, C.; Li, J.; Li, D.; Zheng, M. Evaluation Criteria, Major Types, Characteristics and Resource Prospects of Tight Oil in China. *Pet. Res.* **2016**, *1*, 1–9. [\[CrossRef\]](#)
40. Hinkle, A.; Batzle, M. Heavy Oils: A Worldwide Overview. *Lead. Edge* **2006**, *25*, 742–749. [\[CrossRef\]](#)
41. Santos, R.G.; Loh, W.; Bannwart, A.C.; Trevisan, O.V. An Overview of Heavy Oil Properties and Its Recovery and Transportation Methods. *Braz. J. Chem. Eng.* **2014**, *31*, 571–590. [\[CrossRef\]](#)
42. Guo, K.; Li, H.; Yu, Z. In-Situ Heavy and Extra-Heavy Oil Recovery: A Review. *Fuel* **2016**, *185*, 886–902. [\[CrossRef\]](#)
43. Wu, J.X.; Li, S.F.; Li, Q.F.; Yan, F.; Zhou, Q.L.; Ma, S.; Zhang, Y.H.; Zhao, S.Q.; Shi, Q. Characterization of Chemical Composition of High Viscosity Heavy Oils: Macroscopic Properties, and Semi-Quantitative Analysis of Molecular Composition Using High-Resolution Mass Spectrometry. *Pet. Sci.* **2024**, *21*, 3612–3620. [\[CrossRef\]](#)
44. Lam-Maldonado, M.; Aranda-Jiménez, Y.G.; Arvizu-Sanchez, E.; Melo-Banda, J.A.; Díaz-Zavala, N.P.; Pérez-Sánchez, J.F.; Suarez-Dominguez, E.J. Extra Heavy Crude Oil Viscosity and Surface Tension Behavior Using a Flow Enhancer and Water at Different Temperatures Conditions. *Heliyon* **2023**, *9*, e12120. [\[CrossRef\]](#) [\[PubMed\]](#)
45. Dehkordi, J.A.; Jafari, A.; Sabet, S.A.; Karami, F. Kinetic Studies on Extra Heavy Crude Oil Upgrading Using Nanocatalysts by Applying CFD Techniques. *Chin. J. Chem. Eng.* **2018**, *26*, 343–355. [\[CrossRef\]](#)
46. Banerjee, D.K. *Oil Sands, Heavy Oil and Bitumen—From Recovery to Refinery*; PennWell Corporation: Tulsa, OK, USA, 2012.
47. de Klerk, A. Unconventional Oil: Oilsands. In *Future Energy: Improved, Sustainable and Clean Options for Our Planet*; Letcher, T., Ed.; Elsevier: Amsterdam, The Netherlands, 2020.
48. Vandenbroucke, M. Kerogen: From Types to Models of Chemical Structure. *Oil Gas Sci. Technol.* **2003**, *58*, 243–269. [\[CrossRef\]](#)
49. Vandenbroucke, M.; Largeau, C. Kerogen Origin, Evolution and Structure. *Org. Geochem.* **2007**, *38*, 719–833. [\[CrossRef\]](#)
50. Donadelli, J.A.; Pineda, J.; Comerio, M.; Smal, C.; Erra, G.; Acosta, R.H.; Delfa, G.M. Natural and Laboratory-Induced Maturation of Kerogen from the Vaca Muerta Formation: A Comparison Study. *Org. Geochem.* **2023**, *185*, 104690. [\[CrossRef\]](#)
51. Kumar, R.; Voolapalli, R.K.; Upadhyayula, S. Prediction of Crude Oil Blends Compatibility and Blend Optimization for Increasing Heavy Oil Processing. *Fuel Process. Technol.* **2018**, *177*, 309–327. [\[CrossRef\]](#)
52. Bambinek, K.; Przyjazny, A.; Boczkaj, G. Compatibility of Crude Oil Blends—Processing Issues Related to Asphaltene Precipitation, Methods of Instability Prediction—A Review. *Ind. Eng. Chem. Res.* **2023**, *62*, 2–15. [\[CrossRef\]](#)
53. Rogel, E.; Hench, K.; Miao, T.; Lee, E.; Dickakian, G. Evaluation of the Compatibility of Crude Oil Blends and Its Impact on Fouling. *Energy Fuels* **2018**, *32*, 9233–9242. [\[CrossRef\]](#)
54. Jayaraman, A.; Singh, H.; Lefebvre, Y. Naphthenic Acid Corrosion in Petroleum Refineries. A Review. *Oil Gas Sci. Technol. Rev. IFP* **1986**, *41*, 265. [\[CrossRef\]](#)

55. Al-Moubaraki, A.H.; Obot, I.B. Corrosion Challenges in Petroleum Refinery Operations: Sources, Mechanisms, Mitigation, and Future Outlook. *J. Saudi Chem. Soc.* **2021**, *25*, 101370. [CrossRef]
56. Riazi, M.R.; Daubert, T.E. Prediction of Molecular-Type Analysis of Petroleum Fractions and Coal Liquids. *Ind. Eng. Chem. Process Des. Dev.* **1986**, *25*, 1009–1015. [CrossRef]
57. Dhulesia, H. New Correlations Predict FCC Feed Characterizing Parameters. *Oil Gas J.* **1986**, *84*, 51–54.
58. Choudhary, T.V.; Meier, P.F. Characterization of Heavy Petroleum Feedstocks. *Fuel Process. Technol.* **2008**, *89*, 697–703. [CrossRef]
59. Abutaiya, M.I.L.; Alhammedi, A.A.; Sisco, C.J.; Vargas, F.M. Aromatic Ring Index (ARI): A Characterization Factor for Nonpolar Hydrocarbons from Molecular Weight and Refractive Index. *Energy Fuels* **2021**, *35*, 1113–1119. [CrossRef]
60. Shishkova, I.; Stratiev, D.; Kolev, I.V.; Nenov, S.; Nedanovski, D.; Atanassov, K.; Ivanov, V.; Ribagin, S. Challenges in Petroleum Characterization—A Review. *Energies* **2022**, *15*, 7765. [CrossRef]
61. Riazi, M.R. Characteristics of Heavy Fractions for Design and Operation of Upgrading Related Processes. In Proceedings of the AIChE Annual Meeting, San Francisco, CA, USA, 3–8 November 2013.
62. Adeyemi, M.A. Analysis of Sulfur Content in Selected Crude Oils in the World. In *Contemporary Developments in Hydraulic Fracturing*; Imo-Imo Israel Eshiet, K., Ed.; IntechOpen: Rijeka, Croatia, 2024.
63. Mohammadi, M.; Khanmohammadi Khorrami, M.; Vatanparast, H.; Karimi, A.; Sadrara, M. Classification and Determination of Sulfur Content in Crude Oil Samples by Infrared Spectrometry. *Infrared Phys. Technol.* **2022**, *127*, 104382. [CrossRef]
64. Bacon, R.; Tordo, S. *Crude Oil Price Differentials and Differences in Oil Qualities: A Statistical Analysis*; Technical Paper No. 81; ESMAP: Washington, DC, USA, 2005. Available online: https://www.esmap.org/sites/default/files/esmap-files/08105.Technical%20Paper_Crude%20Oil%20Price%20Differentials%20and%20Differences%20in%20Oil%20Qualities%20A%20Statistical%20Analysis.pdf (accessed on 12 December 2025).
65. Yeung, T.W. Evaluating Opportunity Crude Processing. *PTQ* **2006**, *Q4*, 93–96.
66. Ma, M. Kerogen: Geochemical and Energetic Significance in Geological Formations. *Adv. Resour. Res.* **2023**, *3*, 108–126. [CrossRef] [PubMed]
67. Liu, K.; Qi, H.; Wang, Z.; Liu, B.; Wang, Y.; Zhang, Z.; Zhang, H.; Yang, R.; Jiang, L.; Ostadhassan, M. The Organic Matrix: An in-Depth Review of Kerogen and Its Significance. *Fuel* **2025**, *397*, 135493. [CrossRef]
68. Hutton, A.; Bharati, S.; Robl, T. Chemical and Petrographic Classification of Kerogen/Macerals. *Energy Fuels* **1994**, *8*, 1478–1488. [CrossRef]
69. van den Berg, F.G.A.; Heijnis, R.M.A.; Stamps, P.A.; Kramer, P.A. A Geochemical Framework for Understanding Residue Properties. *Pet. Sci. Technol.* **2003**, *21*, 449–460. [CrossRef]
70. van den Berg, F.G.A.; Kapusta, S.D.; Ooms, A.C.; Smith, A.J. Fouling and Compatibility of Crudes as Basis for a New Crude Selection Strategy. *Pet. Sci. Technol.* **2003**, *21*, 557–568. [CrossRef]
71. Kremer, L.N. Crude Oil and Quality Variations. *Pet. Technol. Q.* **2004**, *9*, 87–97.
72. Alsayoo, L.; Bin Shams, M. The Role of Crude Oil Selection in Enhancing the Profitability of a Local Refinery with Lube Hydro-Processing Capacity. *Chem. Eng. Res. Des.* **2022**, *185*, 146–162. [CrossRef]
73. Sayles, S.; Routt, D.M. Unconventional Crude Oil Selection and Compatibility. 2011. Available online: <https://cdn.digitalrefining.com/data/articles/file/488759177.pdf> (accessed on 6 June 2026).
74. Stratiev, D.; Shiskova, I.; Toteva, V.; Georgiev, G.; Dinkov, R.; Kolev, I.; Petrov, I.; Argirov, G.; Bureva, V.; Ribagin, S.; et al. Experience in Processing Alternative Crude Oils to Replace Design Oil in the Refinery. *Resources* **2024**, *13*, 86. [CrossRef]
75. Stratiev, D.; Dinkov, R.; Shiskova, I.; Nedelchev, A.; Kolev, I.; Argirov, G.; Sotirov, S.; Sotirova, E.; Bureva, V.; Atanassov, K.; et al. Feed Variability Effect on Performance of a Commercial Residue Hydrocracker. *Processes* **2025**, *13*, 3486. [CrossRef]
76. Schempp, P.; Preuß, K.; Tröger, M. About the Correlation between Crude Oil Corrosiveness and Results from Corrosion Monitoring in an Oil Refinery. *Corrosion* **2016**, *72*, 843–855. [CrossRef] [PubMed]
77. Barros, E.V.; Filgueiras, P.R.; Lacerda, V.; Rodgers, R.P.; Romão, W. Characterization of Naphthenic Acids in Crude Oil Samples—A Literature Review. *Fuel* **2022**, *319*, 123775. [CrossRef]
78. Lucke, E.; Ronces, E.A. *Leveraging Synergies Between Refining and Petrochemical Processes*, 1st ed.; CRC Press: Boca Raton, FL, USA, 2020.
79. Singh, H. Classification of crude oils from refiner's view point. Methods and significance. *Erdoel Kohle Erdgas Petrochem.* **1988**, *41*, 458–463.
80. Al-Dahhan, W.H.; Mahmood, S.M.A. Classification of Crude Oils and Its Fractions on the Basis of Paraffinic, Naphthenic and Aromatics. *ANJS* **2019**, *22*, 35–42. [CrossRef]
81. Vakili-Nezhaad, G.R.; Modarress, H. A New Characterization Factor for Hydrocarbons and Petroleum Fluids Fractions. *Oil Gas Sci. Technol. Rev. IFP* **2002**, *57*, 149–154. [CrossRef]
82. Mohammadi, A.; Omidkhan, M.; Karimzadeh, R.; Haghtalab, A. Structural Modeling of Petroleum Fractions Based on Mixture Viscosity and Watson K Factor. *Korean J. Chem. Eng.* **2013**, *30*, 465–473. [CrossRef]

83. Meier, P.F.; Ghonasgi, D.B.; Wardinsky, M. Method for Characterizing Residual Crude Oil and Petroleum Fractions. U.S. Patent 6,275,776 B1, 14 August 2001.
84. Smith, H.M. *Correlation Index to Aid in Interpreting Crude-Oil Analyses*; United States Bureau of Mines Technical Paper 610; Government Printing Office: Washington, DC, USA, 1940; pp. 1–34.
85. Mallison, H. Aufteilung von Steinkohlenteer und Pech. *Bitum. Teere Asph. Pech.* **1950**, *1*, 313–317.
86. Yashchenko, I.G.; Polishchuk, Y.M. Classification Approach to Assay of Crude Oils with Different Physicochemical Properties and Quality Parameters. *Pet. Chem.* **2019**, *59*, 1161–1168. [\[CrossRef\]](#)
87. Van Krevelen, D. Graphical-statistical method for the study of structure and reaction processes of coal. *Fuel* **1950**, *29*, 269–284.
88. Laszakovits, J.R.; MacKay, A.A. Data-based chemical class regions for Van Krevelen diagrams. *J. Am. Soc. Mass Spectrom.* **2021**, *33*, 198–202. [\[CrossRef\]](#) [\[PubMed\]](#)
89. Wang, S.; Wang, Y.; Shi, Z.; Sun, K.; Wen, Y.; Niedzwiecki, L.; Pan, R.; Xu, Y.; Zaini, I.N.; Jagodzińska, K.; et al. Van Krevelen diagrams based on machine learning visualize feedstock-product relationships in thermal conversion processes. *Commun. Chem.* **2023**, *6*, 273. [\[CrossRef\]](#) [\[PubMed\]](#)
90. van den Berg, F.G.A. Origin and Formation of Crude Oils a Geochemical Approach. In Proceedings of the LUKOIL Neftohim Burgas, Burgas, Bulgaria, 11 September 2024.
91. Niu, Z.; Meng, W.; Wang, Y.; Wang, X.; Li, Z.; Wang, J.; Liu, H.; Wang, X. Characteristics of Trace Elements in Crude Oil in the East Section of the South Slope of Dongying Sag and Their Application in Crude Oil Classification. *J. Pet. Sci. Eng.* **2022**, *209*, 109833. [\[CrossRef\]](#)
92. Guzmán-Osorio, F.J.; Domínguez-Rodríguez, V.I.; Adams, R.H.; Lobato-García, C.E.; Guerrero-Peña, A.; Barajas-Hernández, J.R. Classification of Petroleum Origin and Integrity by FTIR. *Egypt. J. Pet.* **2021**, *30*, 63–67. [\[CrossRef\]](#)
93. Tao, K.; Cao, J.; Wang, Y.; Mi, J.; Ma, W.; Shi, C. Chemometric Classification of Crude Oils in Complex Petroleum Systems Using T-Distributed Stochastic Neighbor Embedding Machine Learning Algorithm. *Energy Fuels* **2020**, *34*, 5884–5899. [\[CrossRef\]](#)
94. Chiaberge, S.; Fiorani, T.; Savoini, A.; Bionda, A.; Ramello, S.; Pastori, M.; Cesti, P. Classification of Crude Oil Samples through Statistical Analysis of APPI FTICR Mass Spectra. *Fuel Process. Technol.* **2013**, *106*, 181–185. [\[CrossRef\]](#)
95. Asif, M.; Fazeelat, T. Petroleum Geochemistry of the Potwar Basin, Pakistan: II—Oil Classification Based on Heterocyclic and Polycyclic Aromatic Hydrocarbons. *Appl. Geochem.* **2012**, *27*, 1655–1665. [\[CrossRef\]](#)
96. Zhao, R.; Yuan, Y.; He, J.; Lu, W.; Wang, J.; Zhou, G.; Zou, J.; Liu, S. A Novel Crude Oil Classification Approach Based on Average Carbon Number Determination and Case Studies. *Fuel Process. Technol.* **2026**, *282*, 108400. [\[CrossRef\]](#)
97. Sun, P.; Bao, K.; Li, H.; Li, F.; Wang, X.; Cao, L.; Li, G.; Zhou, Q.; Tang, H.; Bao, M. An Efficient Classification Method for Fuel and Crude Oil Types Based on m/z 256 Mass Chromatography by COW-PCA-LDA. *Fuel* **2018**, *222*, 416–423. [\[CrossRef\]](#)
98. Wang, X.; Liu, G.; Wang, F.; Song, Z.; Johnston, S.T.; Sun, M.; Liu, Z. Chemometric Characterization of Crude Oil Biomarker Ratios from the Western Sub-Depression of the Bozhong Depression, Bohai Bay Basin, China. *Mar. Geosci. Energy Resour.* **2026**, *187*, 207671. [\[CrossRef\]](#)
99. Christie, O.H.J.; Esbensen, K.; Meyer, T.; Wold, S. Aspects of Pattern Recognition in Organic Geochemistry. *Org. Geochem.* **1984**, *6*, 885–891. [\[CrossRef\]](#)
100. Peters, K.E.; Moldowan, J.M.; Schoell, M.; Hempkins, W.B. Petroleum Isotopic and Biomarker Composition Related to Source Rock Organic Matter and Depositional Environment. *Org. Geochem.* **1986**, *10*, 17–27. [\[CrossRef\]](#)
101. Wold, S. Chemometrics; What Do We Mean with It, and What Do We Want from It? *Chemom. Intell. Lab. Syst.* **1995**, *30*, 109–115. [\[CrossRef\]](#)
102. Sancho, A.; Ribeiro, J.C.; Reis, M.S.; Martins, F.G. Cluster Analysis of Crude Oils with K-Means Based on Their Physicochemical Properties. *Comput. Chem. Eng.* **2022**, *157*, 107633. [\[CrossRef\]](#)
103. Galtier, O.; Abbas, O.; Le Dréau, Y.; Rebufa, C.; Kister, J.; Artaud, J.; Dupuy, N. Comparison of PLS1-DA, PLS2-DA and SIMCA for Classification by Origin of Crude Petroleum Oils by MIR and Virgin Olive Oils by NIR for Different Spectral Regions. *Vib. Spectrosc.* **2011**, *55*, 132–140. [\[CrossRef\]](#)
104. Sarafdokht, H.; Rabbani, A.R.; Asemani, M. A Novel Multidisciplinary Approach for Crude Oil Classification Based on Structural Characteristics of Asphaltenes. *Sci. Rep.* **2026**, *16*, 4250. [\[CrossRef\]](#) [\[PubMed\]](#)
105. Barwise, A.J.G. Role of Nickel and Vanadium in Petroleum Classification. *Energy Fuels* **1990**, *4*, 647–652. [\[CrossRef\]](#)
106. Sokolova, I.M.; Abryutina, N.N.; Punanov, V.G.; Petrov, A.A. Chemical Classification of Naphthenic Condensates and Oils. *Org. Geochem.* **1992**, *19*, 1–11. [\[CrossRef\]](#)
107. Yuhan, J.; Ruibo, G.; Dujie, H.; Xiong, C. Classification of Crude Oil and Its Correlation with Terrestrial Plant Inputs across Different Areas in the Xihu Depression, East China Sea Shelf Basin: Insights from Organic Geochemical Evidence. *Front. Earth Sci.* **2025**, *13*, 1627767. [\[CrossRef\]](#)
108. Meng, Y.; Zhang, H.; Ren, C.; Ma, L.; Wang, G.; Jie, Q.; Song, X.; Fu, J.; Zhao, Z. Molecular Geochemical Constraints on Crude Oil Classification and Oil-Source Relationships in the Hexiwu Structural Belt of the Langgu Depression, Bohai Bay Basin, China. *Processes* **2026**, *14*, 739. [\[CrossRef\]](#)

109. Barboza, M.C.d.V.A.; Nascimento, M.H.C.; Folli, G.S.; Botelho, J.R.; de Queiroz Ferreira, R.; Romão, W.; Filgueiras, P.R. Support Vector Machine Ensemble for Crude Oil Classification. *J. Chemom.* **2026**, *40*, e70119. [\[CrossRef\]](#)
110. Oliveira, L.G.; Araújo, K.C.; Barreto, M.C.; Bastos, M.E.P.A.; Lemos, S.G.; Fragoso, W.D. Applications of chemometrics in oil spill studies. *Microchem. J.* **2021**, *166*, 106216. [\[CrossRef\]](#)
111. Alexandrino, G.L.; Tomasi, G.; Kienhuis, P.G.M.; Augusto, F.; Christensen, J.H. Forensic Investigations of Diesel Oil Spills in the Environment Using Comprehensive Two-Dimensional Gas Chromatography–High Resolution Mass Spectrometry and Chemometrics: New Perspectives in the Absence of Recalcitrant Biomarkers. *Sci. Technol.* **2019**, *53*, 550–559. [\[CrossRef\]](#) [\[PubMed\]](#)
112. Mansurova, M.; Johann, S.; Kohlhoff, H.; Rurack, K.; Bartholmai, M.; Bell, J. On-Site Analytical Tool Based on Crude Oil Fluorescence and Chemometrics for the Rapid Determination of the Nature and Essential Properties of Oil Spills. *ACS EST Water* **2024**, *4*, 621–627. [\[CrossRef\]](#)
113. John, G.F. A framework for developing machine learning-based chemical fingerprinting models using large gas chromatograph-mass spectrometer datasets: Application to oil spill residues classification. *Sci. Total Environ.* **2026**, *1015*, 181463. [\[CrossRef\]](#) [\[PubMed\]](#)
114. Li, T.; Yan, D.; Liang, W.; Wei, X. Combining indicators analysis and chemometrics to trace the geographical origin of crude oil. *Pet. Res.* **2023**, *8*, 524–530. [\[CrossRef\]](#)
115. Khelil, I.; Al-Muntaser, A.; Varfolomeev, M.; Hakimi, M.; Suwaid, M.; Saeed, S.; Nurgaliev, D.; Al-Fatesh, A.; Osman, A. Innovations in Crude-Oil Characterization: A Comprehensive Review of LF-NMR Applications. *Energies* **2024**, *17*, 3416. Available online: <https://www.mdpi.com/1996-1073/17/14/3416> (accessed on 13 May 2026).
116. Stratiev, D.; Yordanov, D.; Georgiev, G.; Shishkova, I. Current Cases in the Oil Refining Practice of LUKOIL Neftochim Burgas. *Ind. Technol.* **2026**, *13*, 102–118.
117. Shishkova, I.; Stratiev, D.; Kirov, P.; Dinkov, R.; Sotirov, S.; Sotirova, E.; Bureva, V.; Atanassov, K.; Toteva, V.; Vasilev, S.; et al. Root Cause Analysis for Observed Increased Sedimentation in a Commercial Residue Hydrocracker. *Processes* **2025**, *13*, 674. [\[CrossRef\]](#)
118. Stratiev, D.; Dinkov, R.; Shishkova, I.; Sharafutdinov, I.; Ivanova, N.; Mitkova, M.; Yordanov, D.; Rudnev, N.; Stanulov, K.; Artemiev, A.; et al. What Is behind the High Values of Hot Filtration Test of the Ebullated Bed Residue H-Oil Hydrocracker Residual Oils? *Energy Fuels* **2016**, *30*, 7037–7054. [\[CrossRef\]](#)
119. Stratiev, D.; Shishkova, I.; Georgiev, G.; Dinkov, R.; Nedelchev, A.; Nikolova, R.; Veli, A.; Bureva, V.; Atanassov, K.; van den Berg, F.; et al. The Incompatibility Pitfall in Refining Opportunity Crude Oils. *Processes* **2025**, *13*, 593. [\[CrossRef\]](#)
120. Atanassov, K. *Intuitionistic Fuzzy Logics*; Springer: Cham, Switzerland, 2017.
121. Atanassov, K. *Index Matrices: Towards an Augmented Matrix Calculus*; Springer: Cham, Switzerland, 2014.
122. Atanassov, K.; Mavrov, D.; Atanassova, V. Intercriteria decision making: A new approach for multicriteria decision making, based on index matrices and intuitionistic fuzzy sets. In *Issues in Intuitionistic Fuzzy Sets and Generalized Nets, Volume 11*; Atanassov, K., Kacprzyk, J., Krawczak, M., Szmidt, E., Eds.; Warsaw School of Information Technology: Warsaw, Poland, 2014; pp. 1–8.
123. Atanassov, K.; Atanassova, V.; Gluhchev, G. Intercriteria Analysis: Ideas and Problems. *Notes Intuitionistic Fuzzy Sets* **2015**, *21*, 81–88.
124. Roeva, O.; Zoteva, D. Model Identification of E. Coli Cultivation Process Applying Hybrid Crow Search Algorithm. *Fermentation* **2024**, *10*, 12. [\[CrossRef\]](#)
125. Andreev, N.; Atanassova, V. InterCriteria Analysis of the Blood Group Distribution of Patients of Saint Anna Hospital in 2015–2019. In *Advances and New Developments in Fuzzy Logic and Technology—Selected Papers from IWIFSGN’2019—The Eighteenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets Held on October 24–25, 2019 in Warsaw, Poland*; Atanassov, K.T., Atanassova, V., Kacprzyk, J., Kałusko, A., Krawczak, M., Owsiniński, J.W., Sotirov, S.S., Sotirova, E., Szmidt, E., Zadrozny, S., Eds.; Springer: Cham, Switzerland, 2021; pp. 158–165. [\[CrossRef\]](#)
126. Atanassova, V.; Andreev, N.; Dimitriev, A. ABO System Blood Groups Distribution in Bulgaria, Based on a Dataset of the Patients of the University Hospital “Saint Anna”, Sofia, Bulgaria, from 2015 to 2021. In *Recent Contributions to Bioinformatics and Biomedical Sciences and Engineering. BioInfoMed 2022. Lecture Notes in Networks and Systems*; Sotirov, S., Pencheva, T., Kacprzyk, J., Atanassov, K.T., Sotirova, E., Ribagin, S., Eds.; Springer: Cham, Switzerland, 2023; Volume 658, pp. 72–83. [\[CrossRef\]](#)
127. Atanassova, V.; Andreev, N.; Dimitriev, A. InterCriteria Analysis of the Geographic Distribution of the ABO System Blood Groups in the Patients of the University Hospital “Saint Anna”, Sofia, Bulgaria, from 2015 to 2021. In *Recent Contributions to Bioinformatics and Biomedical Sciences and Engineering. BioInfoMed 2022. Lecture Notes in Networks and Systems*; Sotirov, S., Pencheva, T., Kacprzyk, J., Atanassov, K.T., Sotirova, E., Ribagin, S., Eds.; Springer: Cham, Switzerland, 2023; Volume 658, pp. 84–97. [\[CrossRef\]](#)
128. Georgieva, V.; Angelova, N.; Roeva, O.; Pencheva, T. Intercriteria Analysis of Wastewater Treatment Quality. *J. Int. Sci. Publ. Ecol. Saf.* **2016**, *10*, 365–376.
129. Atanassova, V.; Doukovska, L.; Karastoyanov, D.; Čapkovič, F. Intercriteria Decision Making Approach to EU Member States Competitiveness Analysis: Trend Analysis. In *Intelligent Systems’2014. Advances in Intelligent Systems and Computing*; Angelov, P., Atanassov, K.T., Doukovska, L., Hadjiski, M., Jotsov, V., Kacprzyk, J., Filev, D., Sotirov, S., Szmidt, E., Zadrozny, S., Eds.; Springer: Cham, Switzerland, 2015; Volume 322, pp. 107–115. [\[CrossRef\]](#)

130. Atanassova, V.; Doukovska, L.; Kacprzyk, A.; Sotirova, E.; Radeva, I.; Vassilev, P. InterCriteria Analysis of the Global Competitiveness Reports: From Efficiency- to Innovation-Driven Economies. *J. Mult.-Valued Log. Soft Comput.* **2018**, *31*, 469–494.
131. Doukovska, L.; Atanassova, V.; Shahpazov, G.; Čapkovic, F. InterCriteria Analysis Applied to Various EU Enterprises. In *Proceedings of the Fifth International Symposium on Business Modeling and Software Design—BMSD*; Shishkov, B., Ed.; SciTePress: Setúbal, Portugal, 2015; Volume 1, pp. 284–291. [[CrossRef](#)]
132. Atanassova, V.; Roeva, O. Computational Complexity and Influence of Numerical Precision on the Results of InterCriteria Analysis in the Decision Making Process. *Notes Intuitionistic Fuzzy Sets* **2018**, *24*, 53–63. [[CrossRef](#)]
133. Fidanova, S.; Atanassova, V.; Roeva, O. Ant Colony Optimization Application to GPS Surveying Problems: InterCriteria Analysis. In *Uncertainty and Imprecision in Decision Making and Decision Support: Cross-Fertilization, New Models and Applications. IWIFSGN 2016. Advances in Intelligent Systems and Computing*; Atanassov, K.T., Atanassova, V., Kacprzyk, J., Kałuszko, A., Krawczak, M., Owsiniński, J.W., Sotirov, S.S., Sotirova, E., Szmidt, E., Zadrozny, S., Eds.; Springer: Cham, Switzerland, 2018; Volume 559, pp. 251–264. [[CrossRef](#)]
134. Parvathi, R.; Atanassova, V.; Doukovska, L.; Yuvapriya, C.; Indhurekha, K. InterCriteria Analysis of Rankings of Indian Universities. *Notes Intuitionistic Fuzzy Sets* **2018**, *24*, 99–109. [[CrossRef](#)]
135. Mavrov, D. Software for InterCriteria Analysis: Implementation of the Main Algorithm. *Notes Intuitionistic Fuzzy Sets* **2015**, *21*, 77–86.
136. Mavrov, D. Software for InterCriteria Analysis: Working with the Results. *Annu. Inform. Sect. Union Sci. Bulg.* **2015**, *8*, 37–44.
137. Ikonov, N.; Vassilev, P.; Roeva, O. ICRAData—Software for InterCriteria Analysis. *Int. J. Bioautom.* **2018**, *22*, 1–10. [[CrossRef](#)]
138. Doukovska, L.; Atanassova, V.; Sotirova, E.; Vardeva, I.; Radeva, I. Defining consonance thresholds in intercriteria analysis: An overview. In *Intuitionistic Fuzziness and Other Intelligent Theories and Their Applications*; Hadjiski, M., Atanassov, K., Eds.; Springer: Cham, Switzerland, 2019; Volume 757, pp. 161–179, Studies in Computational Intelligence. [[CrossRef](#)] [[PubMed](#)]
139. Atanassova, V. Interpretation in the Intuitionistic Fuzzy Triangle of the Results, Obtained by the InterCriteria Analysis. In *Proceedings of the Proceedings of the 2015 Conference of the International Fuzzy Systems Association and the European Society for Fuzzy Logic and Technology*; Atlantis Press: Dordrecht, The Netherlands, 2015; Volume 89, pp. 1369–1374. [[CrossRef](#)]
140. Atanassova, V.; Vardeva, I.; Sotirova, E.; Doukovska, L. Traversing and Ranking of Elements of an Intuitionistic Fuzzy Set in the Intuitionistic Fuzzy Interpretation Triangle. In *Novel Developments in Uncertainty Representation and Processing. Advances in Intelligent Systems and Computing*; Atanassov, K.T., Kacprzyk, O.C.J., Melin, M.K.P., Sotirova, S.S.E., De Tré, E.S.G., Zadrozny, S., Eds.; Springer: Cham, Switzerland, 2016; Volume 401, pp. 161–174. [[CrossRef](#)]
141. Al-Muftah, A. Unified Field Compositional Fluid Model for the Bahrain Field. In *Proceedings of the SPE Middle East Oil and Gas Show and Conference, Manama, Kingdom of Bahrain, 18–21 March 2019*. [[CrossRef](#)]
142. Speight, J.G. Bureau of Mines Correlation Index. In *Rules of Thumb for Petroleum Engineers*; Scrivener Publishing LLC: Beverly, MA, USA, 2017; p. 101. [[CrossRef](#)]
143. Navarro, U.; Ni, M.; Orlicki, D. Understanding FCC Feeds and Benefits to Refinery Operation. Available online: <https://www.digitalrefining.com/article/1001054/understanding-fcc-feeds-and-benefits-to-refinery-operation> (accessed on 25 March 2025).
144. Goma, S.; Salem, K.G.; El-hoshoudy, A.N. Enhanced Heavy and Extra Heavy Oil Recovery: Current Status and New Trends. *Petroleum* **2024**, *10*, 399–410. [[CrossRef](#)]
145. Stratiev, D.; Shishkova, I.; Dinkov, R.; Kolev, I.; Argirov, G.; Ivanov, V.; Ribagin, S.; Atanassova, V.; Atanassov, K.; Stratiev, D.; et al. InterCriteria Analysis to Diagnose the Reasons for Increased Fouling in a Commercial Ebullated Bed Vacuum Residue Hydrocracker. *ACS Omega* **2022**, *7*, 30462–30476. [[CrossRef](#)] [[PubMed](#)]
146. Gary, J.H.; Handwerk, G.E.; Kaiser, M.J. *Petroleum Refining Technology and Economics*, 5th ed.; CRC Press: Boca Raton, FL, USA, 2007; pp. 16–17.

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