GEOL. CROAT.	49/2	237 - 242	6 Figs.	5 Tabs.		ZAGREB 1996

Scientific paper

Production Characteristics and Reservoir Quality at the Ivanić Oil Field (Croatia) Predicted by Machine Learning System

PROCEEDINGS

Zvonimir **HERNITZ**[1], Miro **ĐUREKOVIĆ**[2] and Josip **CRNIČKI**[3]

Key words: Ivanić oil field, Reservoir quality, Prediction of oil production, Machine learning system, Expert systems.

Abstract

At the Ivanić oil field, hydrocarbons are accumulated in fine to medium grained litharenites of the Ivanić-Grad Formation (Iva-sandstones member) of Upper Miocene age. Reservoir rocks are divided into eight depositional (production) units (i_I-i_{VIII}). Deposits of each unit are characterized by their own reservoir quality parameters (porosity, horizontal permeability, net pay...). Production characteristics of 30 wells have been studied by a simple statistical method. Two major production well categories ("good producers" and "bad producers") have been found. The contribution of each depositional unit to the total production of an individual well was studied by using a machine learning system which can serve as an expert system shell. The results have shown that:

1) the most important factors affecting the total hydrocarbon production of each well are horizontal permeability and net pay thickness of the depositional units i_V, i_{IV} and i_{III},
2) after 20 wells had been drilled during the primary recovery period it was possible to predict the production category of a well to be drilled in the future with a reliability of 80%.

1. INTRODUCTION

The Ivanić oil field is situated in the north-western part of the Republic of Croatia (Fig. 1). The field was discovered in 1962 on drilling the Iva-2 well.

Hydrocarbons have been accumulated in fine to medium-grained litharenites (Ivanić-Grad Formation, Iva-sandstones member) of Upper Miocene age. The trap is of structural origin (an anticline striking from north-west to south-east). The structure top depth ranges from -1500 m to -1600 m. The first phase of reservoir development was completed in 1966. Hydrocarbon reserves include oil, dissolved gas and a small amount of gas in a gas cap. The field mainly produces under a dissolved-gas drive. The primary recovery period has been characterized by a rapid decrease of reservoir pressure and by an increase of GOR. In 1972, the secondary recovery period (waterflooding) started.

According to the genetic stratigraphic sequence concept (GALLOWAY, 1989) reservoir rocks have been divided into eight depositional events (units) named i_I-i_{VIII} (ĐUREKOVIĆ, 1995; Fig. 2).

The Ivanić oil field produces from depositional units i_{III}-i_{VII}. Stratigraphic and depositional analysis, performed by applying the total and net pay thickness, permeability and porosity criteria, have shown that reservoir rocks are of better quality in the south-west part of the field. An elongated zone of better reservoir quality, strikes from the north-west to south-east and coincides with the palaeodrainage pattern (ĐUREKOVIĆ, 1995).

Well production rate is related to the reservoir quality. Generally, the total well production rate can be defined as a function of individual depositional unit production. Deposits of each unit have been characterized by their own reservoir quality parameters (total and net pay thickness, permeability, oil saturation...). From a reservoir quality point of view, the purpose of our work is to define the importance of each depositional unit and its contribution to the total well production applying an expert system. Furthermore, we intend to test the role of a machine learning system in predicting well production characteristics.

2. METHODS AND RESULTS

At the first stage of our work we have analyzed the average production behavior of 30 wells during the primary and secondary recovery period. A *Production index* (PRIND) has been calculated for each well taking into account well production rates and production period duration (time). A simple statistical method showed the existence of two production well categories (Table 1).

The first category ("bad producers") includes 13 wells (out of 30). Production index values range from 1.5 to 5.5 during the primary recovery period and from 1.5 to 7.4 in the secondary phase of development. The

[1] University of Zagreb, Faculty of Mining, Geology & Petroleum Engineering, Pierottijeva 6, P.O.Box 186, HR-10000 Zagreb, Croatia.

[2] INA-Naftaplin, Šubićeva 29, HR-10000 Zagreb, Croatia.

[3] Frana Gotovca 13, HR-10010 Zagreb, Croatia.

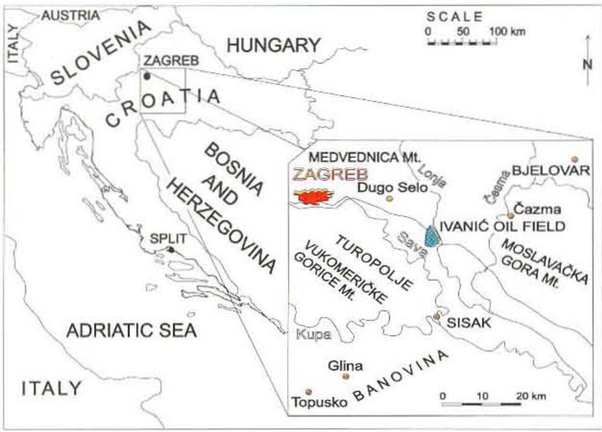

Fig. 1 Location map.

second category ("good producers") includes 17 wells. PRIND values vary from 4.8 to 12.2 in the primary recovery period and from 2.1 to 10.8 in the secondary recovery phase. The main differences between those two categories can be determined from average annual production rates (Figs. 3 and 4; see also Fig. 5 for well locations).

Four reservoir quality parameters (variables) have been analysed for each depositional (production) unit in each well:

- POR - effective porosity (%);
- HPER - horizontal permeability (x10^{-3} μm^2);
- DEF - net pay thickness (m);
- SO - oil saturation (%).

Reservoir quality parameters (20 in total) have been named after the depositional unit number. For example, depositional unit i_{III} has the following variables: 3POR, 3HPER, 3DEF, 3SO; i_{IV} has 4POR, 4HPER etc.

The analysis also included three parameters common for all depositional units in individual wells:

- KNV - oil/water contact depth (m);
- JK - name of depositional unit where oil/water contact has been established;
- SUB - existence of injection well (first neighbour) (Yes/No);

All these variables (23 in total) have been analyzed by a machine learning system named "Assistant Professional" (CESTNIK et al., 1987). It can automatically construct decision trees from examples, and it can serve

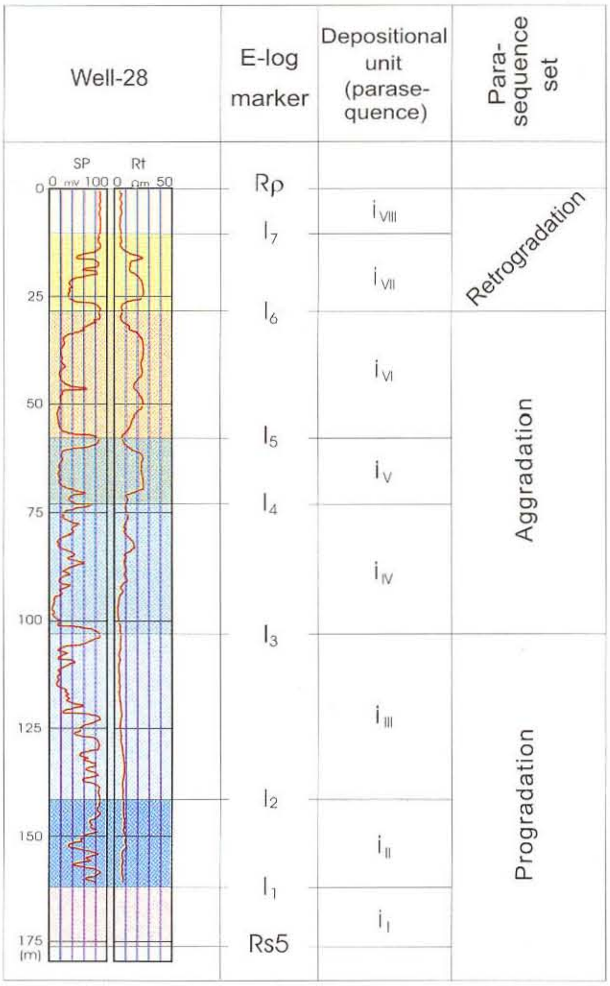

Fig. 2 Depositional units of genetic stratigraphic sequence IVA.

as an expert system shell for the acquired knowledge base (NOVINC, 1992; CRNIČKI et al., 1994). The Assistant Professional expert system is a very flexible computer package which allows engineers to participate in the analysis by selecting the most important variables in decision tree nodes (CRNIČKI, 1989).

During data analysis by the Assistant Professional learning system, several phases were performed which approach the best possible prediction results. This paper discusses four of them:

1) Phase 1 - the learning system automatically generates the rules needed to classify the well in one of two possible production categories. The system used 23 variables for each of 30 wells. A decision dia-

Category (group)	Primary recovery period (1962-1972)		Secondary recovery period (1972-1995)		Number of wells (total 30)	%
	PRIND	average PRIND	PRIND	average PRIND		
I	1.5 - 5.5	3.2	1.5 - 7.4	3.7	13	43.3
II	4.8 - 12.2	8.1	2.1 - 10.8	5.5	17	56.7
				Σ	30	100.0

Table 1 Production index.

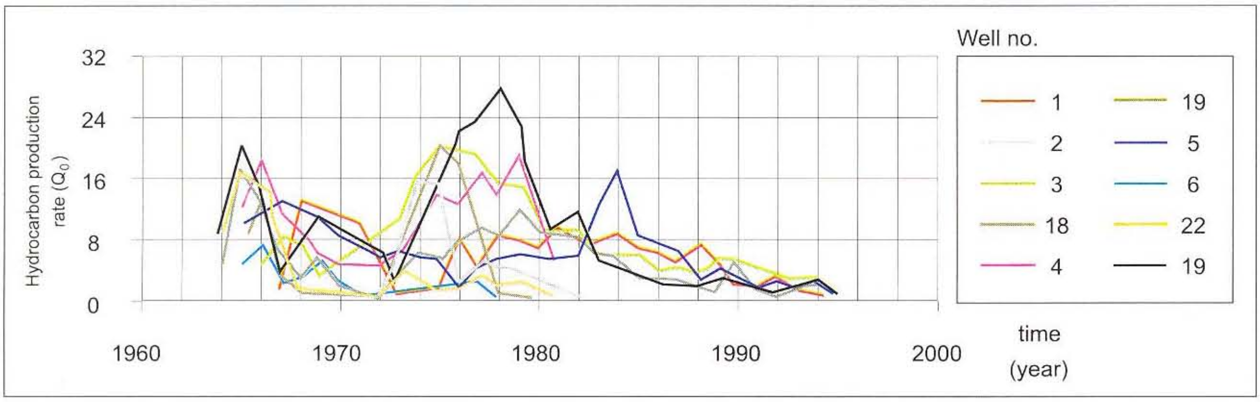

Fig. 3 Hydrocarbon production rate - "bad producers".

gram (Table 2) shows that depositional units i_V, i_{IV} and i_{III} affect the well production rate much more than depositional units i_{VI} and i_{VII}. The most important variables are horizontal permeability and net pay thickness (5HPER, 4DEF, 3DEF). Porosity (POR), well structural position (JK) and depth of oil/water contact are less important, as well as the existence of an injection well (first neighbour) in the vicinity of the producer (SUB).

2) Phase 2 - A defined number of wells (5, 8, 11 and 14 from the total of 30) (Table 3) are selected by random number generation process to be used for a decision diagram reliability test. Then, the expert system was applied to the rest of the wells (non-selected) taking into account acquired knowledge from phase 1 (including a decision diagram and the importance of variables from the tree). Finally, a new decision tree was generated and tested on a cho-

<table>
<tr><td></td><td colspan="10">5HPER</td></tr>
<tr><td></td><td colspan="5">≤ 29.9
4DEF</td><td colspan="5">> 29.9
3DEF</td></tr>
<tr><td></td><td colspan="2">≤ 10.5
5SO</td><td colspan="3">> 10.5
3DEF</td><td>≤ 19.7</td><td colspan="4">> 19.7
7DEF</td></tr>
<tr><td></td><td>≤ 49.5</td><td>> 49.5</td><td>≤ 19.7</td><td colspan="2">> 19.7
JK</td><td></td><td>≤ 2.5</td><td colspan="3">> 2.5
6POR</td></tr>
<tr><td></td><td></td><td></td><td></td><td>≤ 4.5</td><td>> 4.5</td><td></td><td></td><td colspan="2">≤ 20.6
4POR</td><td>> 20.6</td></tr>
<tr><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>≤ 21.7</td><td>> 21.7</td><td></td></tr>
<tr><td>Category</td><td>1</td><td>2</td><td>2</td><td>1</td><td>2</td><td>2</td><td>1</td><td>2</td><td>1</td><td>2</td></tr>
</table>

Table 2 Decision diagram (phase I).

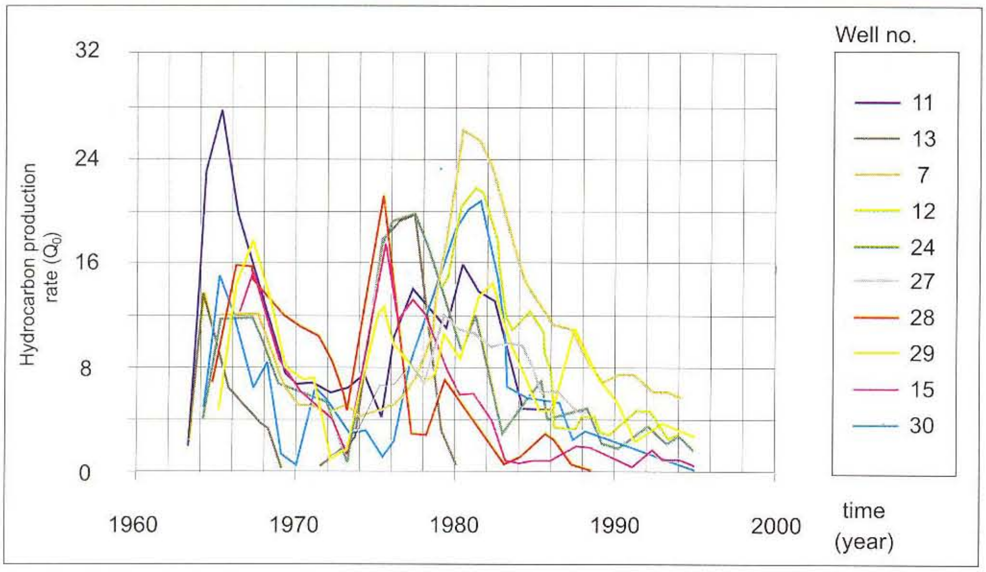

Fig. 4 Hydrocarbon production rate - "good producers".

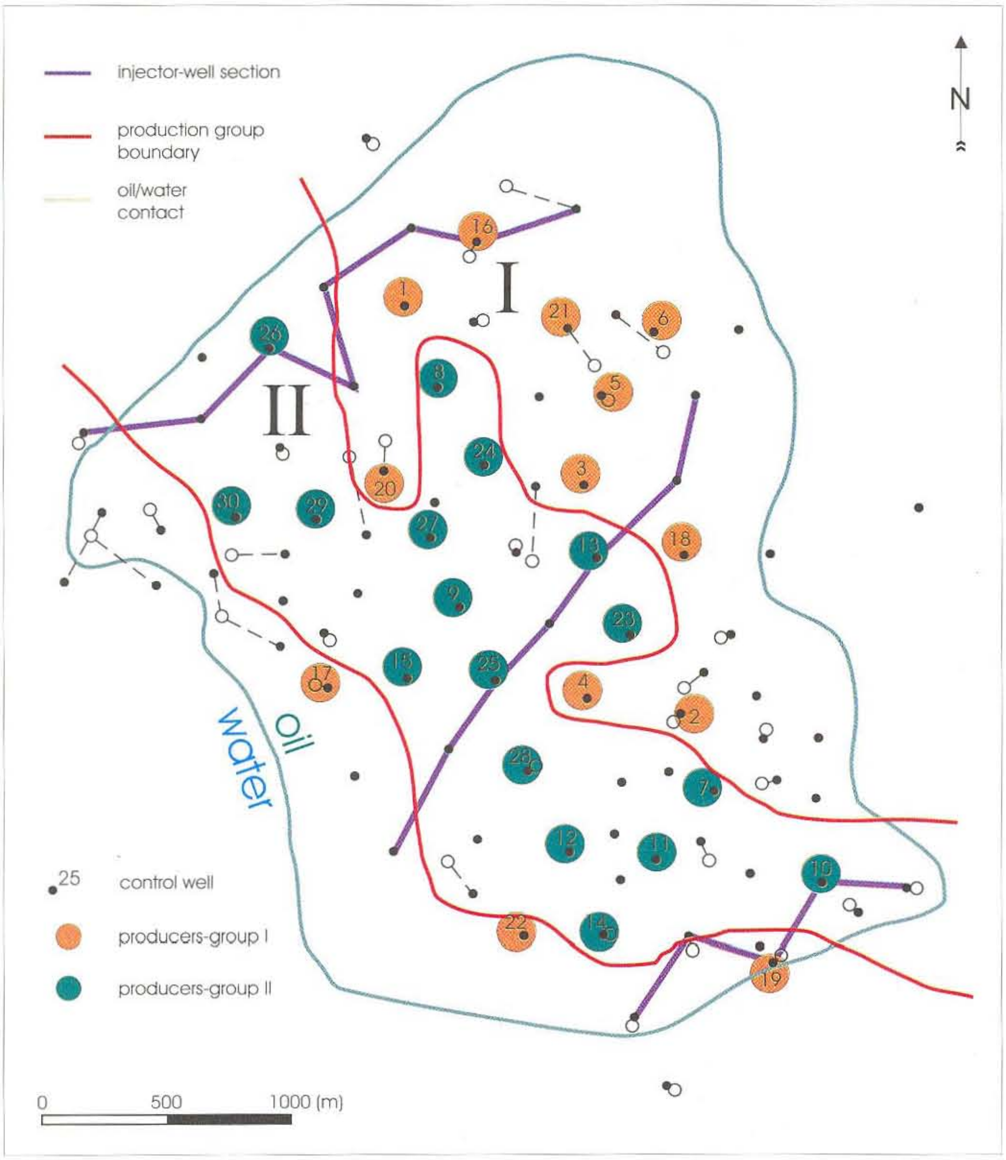

Fig. 5 Production well category and location map.

Number of wells learning	testing	Number of correct answers	Reliability (%)
25	5	5	100.0
22	8	7	85.5
19	11	8	72.7
16	14	10	71.4

Table 3 Reliability of well category prediction (phase 2).

sen test wells. The procedure was repeated three times. Average results are shown in Table 3.

The general conclusion is: prediction reliability is proportional to the number of learning wells. In all cases reliability is greater than 70%.

3) Phase 3 - the expert system followed the same procedure as in phase 2, without taking into account knowledge from phase 1 or phase 2. Table 4 shows the reliability for two different cases. In case *(a)*

Number of wells		Case (a) (without human intervention)		Case (b) (human intervention, fixed variables 5HPER, 4DEF, 3DEF)	
learning	testing	number of correct answers	reliability (%)	number of correct answers	reliability (%)
25	5	3	60.0	3	60.0
22	8	4	50.0	5	62.5
19	11	5	45.0	6	55.0
16	14	6	43.0	7	50.0

Table 4 Reliability of well category prediction (phase 3).

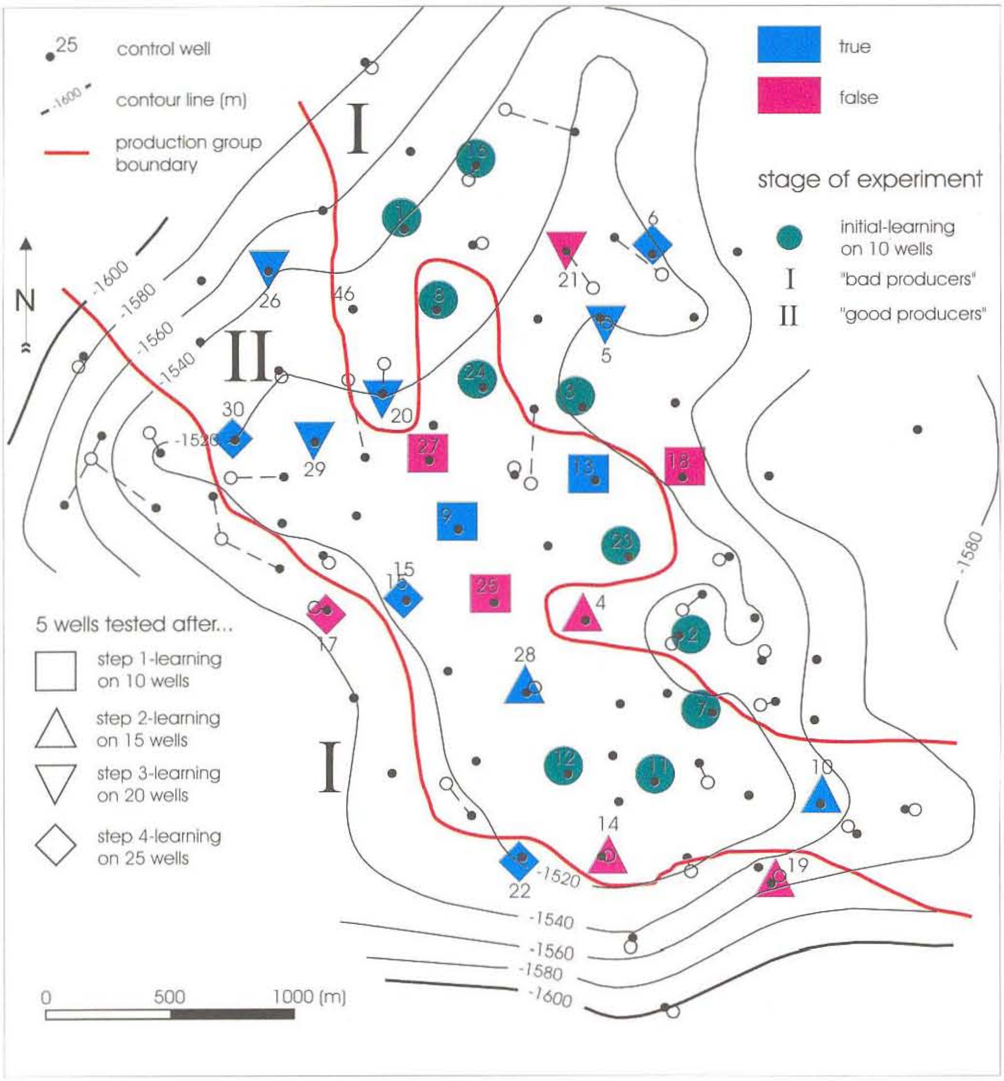

Fig. 6 Succession of reservoir exploration or/and development.

there was no human intervention in decision analysis. In case *(b)* the first two levels (nodes), the most important variables were selected by us (human intervention). Results show that human experience can help the expert system to obtain better results.

4) Phase 4 shows how the machine learning system can be used during reservoir exploration or/and development. At the beginning we selected 10 wells out of 30 according to the drilling succession (well-1 was drilled first, well-2 was drilled after well-1...). The system generates the decision tree automatically from the data base for those 10 wells. Reliability of the decision tree analysis was tested on five wells (planned to be drilled) assuming that we would be able to predict the values of variables needed for prediction from the already known geological situation. The procedure was repeated until 25 learning wells were reached. Results show (Table 5; see also well locations in Fig. 6) that 15-20 wells should be drilled before the expert system can predict the production category of future (planned) well with a reliability of 80%.

Number of wells learning	Number of wells testing	Number of correct answers	Reliability (%)
10	5	2	40.0
15	5	3	60.0
20	5	4	80.0
25	5	4	80.0

Table 5 Reliability of well category prediction (phase 4).

3. CONCLUSIONS

1) A machine learning system can be used in order to predict the significance and contribution of individual production units, to the total well production taking into account their reservoir quality (phase 1).
2) Human intervention based on experience in many cases will help the expert system to obtain better and more reliable results (phases 2 and 3).
3) A machine learning system is of great help in planning reservoir exploration and/or development process by predicting well production behaviour on the basis of the known geological characteristics of

reservoir rocks (phase 4). This gives us an opportunity to predict the minimum number of wells needed to achieve a maximum production effect.

4) Further improvement could be achieved by a similar analysis in 3D space.

5) In the geological decision making process the machine learning systems are able to reduce the number of bad producer wells. It could be recommended to use the described or similar methods as it has importance in the oil-production economy.

4. REFERENCES

CESTNIK, B., KONONENKO, I. & BRATKO, I. (1987): Assistant 86 - a knowledge - elicitation tool for sophisticated users.- In: BRATKO, I. & LAVRAČ, N. (eds.): Progress in Machine Learning. Sigma Press, 31-45, Wilmslow.

CRNIČKI, J. (1989): Knowledge based systems in Geology.- Proceedings of International Conference on Mathematical Methods in Geology, 2, 652-658, Pribřam.

CRNIČKI, J., HERNITZ, Z. & CESTNIK, B. (1994): Oil forecasting in Slavonia (Croatia) by the Assistant Professional Expert System Shell.- Croatian Geotechnical Journal, I/1-2, 13-17, Varaždin.

ĐUREKOVIĆ, M. (1995): Sedimentation and reservoir characteristics of Iva sandstone at the oil field of Ivanić.- Unpublished M.Sc. Thesis, University of Zagreb, 58 p., Zagreb.

GALLOWAY, W.E. (1989): Genetic stratigraphic sequence in Basin Analysis I: Architecture and genesis of flooding-surface bounded depositional Units.- AAPG Bulletin, 73/2, 125-142.

NOVINC, M. (1992): Possibilities for estimation of oil and gas in the eastern part of Drava basin by a machine learning system.- Unpublished M.Sc. Thesis, University of Zagreb, 85 p., Zagreb.