COMPARISON OF SELECTED TRADE CLASSIFICATION ALGORITHMS ON THE WARSAW STOCK EXCHANGE

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Abstract: Empirical equity market microstructure research often requires knowledge about trade sides. It is important to recognize the side that initiates the transaction and to distinguish between the so called buyer- and seller-initiated trades. Unfortunately, most data sets do not identify the trade direction. Therefore, researchers rely on indirect trade classification rules to infer trade sides. The aim of this paper is to implement and compare four trade classification algorithms on the Warsaw Stock Exchange (WSE). The high-frequency data for the selected WSE-listed companies covers the period from January 3, 2005 to June 30, 2015. To check the robustness of empirical results to the choice of sample, three adjacent sub-periods of equal size: the pre-crisis, crisis, and post-crisis period are analysed. The Global Financial Crisis on the WSE is formally established as the period June 2007-February 2009.

Keywords: trade classification algorithms, intraday data, Polish stock market

1. Introduction

The issue of trade direction is important in the market microstructure literature. For example, in order to measure dimensions of liquidity, intra-day liquidity, and imbalance on the order-driven market we have to recognize the side initiating the transaction and to distinguish between the so called buyer- and seller-initiated trades. The classification indicates which of the two participants in the trade, the buyer or the seller, is more eager to trade. When such a distinction does not exist, the trade is labeled as indeterminate [28]. The Warsaw Stock Exchange (WSE) is classified as an order-driven market with an electronic order book, but the information of the best bid and ask prices is not publicly available, (e.g. [16,21]). In fact, even the non-proprietary financial databases that provide information on trades and quotes do not

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identify the trade direction. As a consequence, the researchers rely on indirect trade classification rules to infer trade sides [2]. There are some trade classification procedures described in the literature.

The main goal of this paper is to implement and to compare four trade classification algorithms: the quote rule (QR), the tick rule (TR), the Lee and Ready (LR) [18] and the Ellis, Michaely and O'Hara (EMO) [11] procedures, using high-frequency data for the selected WSE-listed stocks. Based on the paper [16], we have chosen three representative firms from the size groups, specifically: the KGH[3] from the BIG group, the MCI[4] from the MEDIUM group, and the ENP[5] from the SMALL group. We utilize the KGH intra-day data, as the KGH is one of the most liquid WSE-companies. The levels of liquidity for the MCI and ENP are also relatively high in comparison to the securities from the corresponding size groups, e.g. [23]. The comparison of trade classification rules both in the whole sample January 3, 2005-June 30, 2015 and over three adjacent sub-periods of equal size (436 days) [16]: (1) the pre-crisis period September 6, 2005-May 31, 2007, (2) the crisis period June 1, 2007-February 27, 2009, and (3) the post-crisis period March 2, 2009-November 19, 2010, is provided. The Global Financial Crisis on the WSE was formally set based on the papers [24,25], in which the method for direct statistical identification of market states was employed. The empirical results are novel and, to the best of the authors' knowledge, have not been presented in the literature thus far.

The remainder of the study is organized as follows. Section 2 presents a brief literature review concerning the motivation and applications of trade classification algorithms. Section 3 specifies the algorithms employed in the research. In Section 4, we describe the empirical experiment on the Warsaw Stock Exchange. We implement and compare four algorithms using the intra-day transaction data for three WSE-listed companies. The last section encompasses the conducted research with a brief summary.

2. Inferring trade direction: motivation and applications

Traditional capital market approach treats the market aggregation process as a 'black box'. News and information are processed in some obscure fashion and prices adjust to reflect the aggregate effect of this information [19]. However, recent developments

[3] KGHM Polska Miedź S.A.
[4] MCI Management S.A.
[5] ENAP Energoaparatura S.A.

in market microstructure research are beginning to unravel this black box. The increasing availability of intra-day data is opening new frontiers for financial market research, also for the use of observed trades and quotes. The study of observed trades and quotes enables us to obtain new insights about market participants. Unfortunately, most data sets do not identify trade sides. In this context, inferring trade direction from intra-day data is especially worthwhile to conduct because of its applications for a comprehensive analysis of market liquidity.

The main motivation for this study is provided by the growing interest in market liquidity, dimensions of liquidity, and commonality in liquidity that has emerged in the literature over the recent years. As the nature of liquidity is multidimensional, the interpretation of market liquidity causes some problems. A common approach consists in breaking up liquidity into three or four components. Some authors propose three dimensions of liquidity: (1) tightness, (2) depth, and (3) resiliency, e.g. [8], but usually the following four aspects or dimensions are distinguished: (1) trading time, (2) market tightness, (3) market depth, and (4) market resiliency, (e.g. [16,29,33]). However, the analysis of proxies of market dimensions requires the use of high-frequency transaction data, especially including the information about the trade direction. Similarly, the proxies of many intra-day liquidity measures are calculated based on trade and quotes data, (e.g. [6,14,15,23,29,31,33]). Moreover, the order imbalance indicators are approximated based on the information about the number, volume and value of transactions initiated by each side of the market (e.g. [6,7,21]). Notice here that there exists a large empirical financial literature employing the trade classification algorithms on international stock markets, (e.g. [1,2,3,4,5,6,7,9,10,11,12,13,14,17,18,19,20,22,26,27,28,30,32]). On the contrary, research conducted on the Polish stock market is rather scarce, e.g. [21].

3. Trade classification algorithms

The goal of trade classification is to correctly determine the initiator of the transaction [22]. However, a formal definition of a trade initiator is rarely stated in the literature. For example, the so called 'immediacy' definition describes initiators as traders who demand immediate execution, e.g. [19]. According to [22], the initiator of a transaction is the investor (buyer or seller) who placed his/her order last, chronologically (the so called 'chronological' definition). The two definitions are equivalent in many cases. In both definitions, the initiator is the person who caused the transaction to occur. As mentioned in Introduction, there are some trade classification procedures described in the literature: the tick rule, the reverse tick rule, the quote rule, the at the quote rule, the revised quote rule, the Lee-Ready (LR) algorithm, the revised LR algorithm, the Ellis-Michaely-O'Hara (EMO) algorithm, and the Bulk Volume Classification (BVC) methodology. The content of each classification rule is described as follows:

– The tick rule is based on price movements relative to previous trades. If the transaction is above (below) the previous price, then it is a buy (sell). If there is no price change but the previous tick change was up (down), then the trade is classified as a buy (sell) (e.g. [18,20]).
– The reverse tick rule uses the next trade price to classify the current trade. If the next trade occurs on an up-tick or zero up-tick, the current trade is classified as a sell. If the next trade occurs on a down-tick or zero down-tick, the current trade is classified as a buy, (e.g. [18,20]).
– The quote rule classifies a transaction as a buy if the associated trade price is above the midpoint of the bid and ask. If the trade price is below the midpoint quote, then the trade is classified as a sell (e.g. [18,20]).
– The at the quote rule classifies a transaction as a buy if the associated trade price is traded at the asking price. If the trade price is at the bidding price, then the trade is classified as a sell [20].
– The revised quote rule considers the problem of 'no bid or no offer quote'. The trade would be classified as a buy if there is only the bid-side quote and it would be classified as a sell if there is offer-side quote only [20].
– The LR algorithm [18] is a combination of the quote rule and the tick rule. In the first stage the trade is classified according to the quote rule. In the second stage the midpoint transaction is classified according to the tick rule (details in table 1).
– The revised LR algorithm [20] which first adjusts the 'no bid or no offer quote' problems, and then classifies a trade according to the quote rule and finally the tick rule.
– The algorithm proposed by Chakrabarty, Li, Nguyen and Van Ness [2] which is a hybrid of the tick and quote rules. It uses the quote rule when transaction prices are closer to the ask and bid, and the tick rule when transaction prices are closer to the midpoint.
– The EMO algorithm [11] classifies the trades by means of the at the quote rule first and then the tick rule (details in table 1).
– The BVC algorithm [10] aggregates trades over short time intervals or volume intervals and then uses the standardized price change between the beginning and the end of the interval to approximate the percentage of buy and sell volume. Unlike traditional trade classification algorithms that assign trades to be either buys or sells, the BVC approach apportions trades into buy volume and sell volume.

The rules employed in the empirical experiment on the WSE are described in details in table 1. P_t denotes the transaction price at time t. The midpoint price P_t^{mid} at time t is calculated as the arithmetic mean of the best ask price $P_t(a)$ and the best bid price $P_t(b)$ at time t:

$$P_t^{mid} = \frac{P_t(a) + P_t(b)}{2}. \tag{1}$$

The implementation of the quote rule, the tick rule, the LR and EMO procedures is presented in detail (Algorithms 1-4). The accuracy of trade classification algorithms has been examined in many studies, (e.g. [1,2,3,4,10,11,12,18,19,20,22,32]).

Among others, Lee and Radhakrishna [19] report that the active-side of each trade, as identified by the LR rule [18], is generally a good proxy for the frequency, size, and direction of incoming market orders. They use the TORQ[6] database which contains data on NYSE[7] stocks. The authors find that for those trades that can be classified, the LR algorithm is 93% accurate.

Odders-White [22] investigates the performance of the quote, tick and LR methods, using the TORQ data for NYSE stocks. She finds that the quote rule performs relatively well on the transactions that it classifies, misclassifying only 9.1% of the transactions in the sample. The tick rule misclassifies 21.4% of the transactions, while the LR algorithm misclassifies only 15.0% of the transactions. Moreover, she reports success rates of 75%, 79%, and 85%, for the quote, tick and LR rules, respectively.

Ellis, Michaely and O'Hara [11] examine the validity of several trade classification methods for NASDAQ[8] trades. They find that the quote rule, the tick rule, and the LR [18] rule correctly classify 76.4%, 77.66%, and 81.05% of the trades, respectively. The authors develop a new trade classification algorithm (the so called EMO rule, see table 1). For sorting trades into buys and sells, their algorithm achieves an overall success rate of 81.9% in the NASDAQ market.

Finucane [12] employs the tick test, the reverse tick test, and the LR method to classify trades as buys or sells, and he compares the results to the direction of the actual orders, using the TORQ database. The author concludes that for NYSE firms, the tick rule and the LR method have very similar performance accuracy in classifying trades, while the reverse tick test performs substantially worse.

Theissen [32] analyses the accuracy of the tick test and the LR trade classification algorithm on the Frankfurt Stock Exchange (FSE). He reports that the LR method classifies 72.8% of the transactions correctly, and the tick test performs al-

[6] TORQ - Trades, Orders, Reports, and Quotes
[7] NYSE - New York Stock Exchange
[8] NASDAQ - National Association of Securities Dealers Automated Quotations

most equally well. The author stresses that the accuracy of the LR method on the FSE is limited.

Lu and Wei [20] investigate the applicability and accuracy of many trade classification methods on the Taiwan Stock Exchange. They employ the tick, reverse tick, quote, at the quote, and revised quote rules, as well as the LR and the EMO algorithms. The authors proposed their own classification rule - the revised LR algorithm.

However, although a number of alternative algorithms have been developed, the Lee-Ready [18] algorithm remains the most frequently used [3].

Table 1. The quote rule (QR), the tick rule (TR), the Lee-Ready (LR) and Ellis-Michaely-O'Hara (EMO) trade classification algorithms

Rule	Conditions	
	Trade is classified as buyer-initiated	Trade is classified as seller-initiated
QR	If $P_t > P_t^{mid}$	If $P_t < P_t^{mid}$
	If $P_t = P_t^{mid}$ then a trade is not classified.	
TR	If $P_t > P_{t-1}$	If $P_t < P_{t-1}$
	In case $P_t = P_{t-1}$ trade is signed using the previous transaction price. If the sign of the last non-zero price change is positive (negative) then the trade is classified as a buy (a sell).	
LR	I stage	
	If $P_t > P_t^{mid}$	If $P_t < P_t^{mid}$
	If $P_t = P_t^{mid}$ then:	
	II stage	
	If $P_t^{mid} > P_{t-1}$	If $P_t^{mid} < P_{t-1}$
	When $P_t^{mid} = P_{t-1}$, the decision is taken using the sign of the last non-zero price change P_{t-k}. If $P_t > P_{t-k}$ then it is a buy, if $P_t < P_{t-k}$ then it is a sell.	
EMO	I stage	
	If $P_t = P_t(a)$	If $P_t = P_t(b)$
	II stage	
	Trades with prices different from bid and ask prices are categorized by the tick rule. P_t is compared to P_{t-1}: If $P_t > P_{t-1}$ then it is a buy, if $P_t < P_{t-1}$ then it is a sell.	

4. The empirical experiment on the Warsaw Stock Exchange

The high-frequency data 'rounded to the nearest second' available at www.bossa.pl was utilized. The data set contains the opening, high, low and closing (OHLC) prices for the security over one unit of time. Following [21], the transaction price P_t at time

Algorithm 1 The QR trade classification function

Require: $data$ - file with the list of transactions from the earliest to the latest; each transaction is written in a separate $line$;
$line$ - string that contains transaction data and must possess following format:
$[Company\_name], 0, [Date : YYYYMMDD], [TimeOfDay : HHMMSS], O, H, L, C, V;$
$date$ - string that contains date of the previous trade;

Ensure: The QR trade classification function itself returns 3 possibilities:
1, when trade is classified as buyer-initiated;
0, when trade is not classifiable;
-1, when trade is classified as seller-initiated.

int QR(double *open*, double *high*, double *low*, double *close*):
double $mid = (high + low)/2$
if $close > mid$ **then**
    return 1
end if
if $close < mid$ **then**
    return -1
end if
return 0

t was approximated by the close price. Considering that the bid and ask prices are not public information on the WSE, the midpoint price P_t^{mid} at time t was rounded by the arithmetic mean of the lowest price P_t^L and the highest price P_t^H at time t which approximated the best ask price and the best bid price respectively. Then Eq. (1) becomes Eq. (2):

$$P_t^{mid} = \frac{P_t^L + P_t^H}{2}. \tag{2}$$

On the trading days during the period from January 3, 2005 to June 30, 2015 there are 3 959 406 transactions in the KGH data set, 530 697 transactions in the MCI data set, and 87 005 transactions in the ENP data set. Every transaction is assigned using the QR, TR, LR and EMO trade classification algorithms (see Tab. 1). The opening trade is treated as unclassified in the TR, LR and EMO procedures [17]. Of course, there is inevitably some assignment error [6]. Yet, as shown e.g. in [3,11,12,19,22], the proposed algorithms are accurate enough as not to pose serious problems in our large sample study. Tables 2-4 contain empirical results of the comparison of the QR, TR, LR and EMO procedures for the KGH, MCI and ENP intra-day transaction data, in the whole sample and three investigated sub-periods, respectively.

The empirical results presented in Tables 2-4 indicate that the TR and LR algorithms are more appropriate compared to the QR and EMO procedures on the WSE. In the case of the TR and LR methods, the percentage of unclassified transactions is

Algorithm 2 The TR trade classification function

Require: $data$ - file with the list of transactions from the earliest to the latest; each transaction is written in a separate *line*;
line - string that contains transaction data and must possess following format:
$[Company\_name], 0, [Date : YYYYMMDD], [TimeOfDay : HHMMSS], O, H, L, C, V;$
$date$ - string that contains date of the previous trade;
$closes[]$ - dynamic array of previous close prices; it is cleared when next day is to be processed; array allows to insert elements at the end of array $(.push(double))$, clear entire array $(.clear())$ and checking its size $(.size())$;

Ensure: The TR trade classification function itself returns 3 possibilities:
1, when trade is classified as buyer-initiated;
0, when trade is not classifiable;
-1, when trade is classified as seller-initiated.

int TR(double *open*, double *high*, double *low*, double *close*, double[]*closes*):
for $i \leftarrow closes.size() - 1$ **to** 0 **do**
  double $pt = closes[i]$
  if $close - pt < 0$ **then**
    return -1
  end if
  if $close - pt > 0$ **then**
    return 1
  end if
end for
return 0

relatively low. The amount of buyer- and seller-initiated trades is almost equal, with a little predominance of buyer-initiated in all investigated periods. This evidence is consistent with the literature, as some papers demonstrate that short sales are sometimes misclassified as buyer-initiated by trade classification algorithms, e.g. [1]. On the contrary, the applicability and accuracy of the QR and EMO rules is rather low, with a high percentage of unclassified trades in the KGH, MCI and ENP data sets. It is worthwhile to note that the EMO method was proposed for the NASDAQ, which is a hybrid market, while the Warsaw Stock Exchange is classified as an order-driven market. The probable explanation of discrepancies in trade classification results between markets is that stock market structure and trading mechanisms may affect the accuracy of trade classification algorithms.

5. Conclusion

The validity of many market microstructure studies depends on the ability to accurately classify trades as buyer- or seller-initiated. Despite the importance of trade

Table 2. Performance of the QR, TR, LR and EMO trade classification algorithms for the KGH (the BIG group) transaction data from the period January 3, 2005-June 30, 2015

Rule	Total number of trades	Percentage of buyer-initiated trades	Percentage of seller-initiated trades	Percentage of unclassified trades
QR				
whole sample	3 959 406	4.14	4.44	91.42
pre-crisis	390 257	2.03	2.52	95.45
crisis	502 404	5.50	5.37	89.13
post-crisis	635 692	5.45	5.66	88.89
TR				
whole sample	3 959 406	51.13	48.53	0.34
pre-crisis	390 257	50.86	48.36	0.78
crisis	502 404	51.11	48.63	0.26
post-crisis	635 692	52.04	47.78	0.18
LR				
whole sample	3 959 406	51.16	48.51	0.33
pre-crisis	390 257	50.86	48.37	0.77
crisis	502 404	51.17	48.58	0.25
post-crisis	635 692	52.06	47.76	0.18
EMO				
whole sample	3 959 406	4.42	4.15	91.43
pre-crisis	390 257	2.52	2.03	95.45
crisis	502 404	5.37	5.50	89.13
post-crisis	635 692	5.65	5.45	88.90

Table 3. Performance of the QR, TR, LR and EMO trade classification algorithms for the MCI (the MEDIUM group) transaction data from the period January 3, 2005-June 30, 2015

Rule	Total number of trades	Percentage of buyer-initiated trades	Percentage of seller-initiated trades	Percentage of unclassified trades
QR				
whole sample	530 697	6.18	6.49	87.33
pre-crisis	93 563	6.57	7.43	86.00
crisis	93 475	7.90	8.42	83.68
post-crisis	111 170	6.53	6.30	87.17
TR				
whole sample	530 697	50.54	47.70	1.76
pre-crisis	93 563	52.11	46.44	1.45
crisis	93 475	50.32	48.57	1.11
post-crisis	111 170	50.74	48.40	0.86
LR				
whole sample	530 697	50.90	47.36	1.74
pre-crisis	93 563	52.09	46.46	1.45
crisis	93 475	50.79	48.14	1.07
post-crisis	111 170	51.35	47.82	0.83
EMO				
whole sample	530 697	6.46	6.20	87.34
pre-crisis	93 563	7.43	6.57	86.00
crisis	93 475	8.40	7.92	83.68
post-crisis	111 170	6.27	6.60	87.13

Table 4. Performance of the QR, TR, LR and EMO trade classification algorithms for the ENP (the SMALL group) transaction data from the period January 3, 2005-June 30, 2015

Rule	Total number of trades	Percentage of buyer-initiated trades	Percentage of seller-initiated trades	Percentage of unclassified trades
QR				
whole sample	87 005	6.25	6.94	86.81
pre-crisis	37 902	6.15	7.00	86.85
crisis	18 962	7.45	7.99	84.56
post-crisis	8 040	5.65	5.46	88.89
TR				
whole sample	87 005	49.66	44.26	6.08
pre-crisis	37 902	51.93	45.41	2.66
crisis	18 962	50.07	45.70	4.23
post-crisis	8 040	47.43	42.95	9.62
LR				
whole sample	87 005	49.78	44.23	5.99
pre-crisis	37 902	51.92	45.45	2.63
crisis	18 962	50.34	45.53	4.13
post-crisis	8 040	47.77	42.77	9.46
EMO				
whole sample	87 005	6.84	6.21	86.95
pre-crisis	37 902	6.99	6.14	86.87
crisis	18 962	7.90	7.43	84.67
post-crisis	8 040	5.16	5.57	89.27

Algorithm 3 The LR trade classification function

Require: *data* - file with the list of transactions from the earliest to the latest; each transaction is written in a separate *line*;
line - string that contains transaction data and must possess following format:
$[Company\_name], 0, [Date : YYYYMMDD], [TimeOfDay : HHMMSS], O, H, L, C, V$;
$closes[]$ - dynamic array of previous close prices; it is cleared when next day is to be processed; array allows to insert elements at the end of array $(.push(double))$, clear entire array $(.clear())$ and checking its size $(.size())$;

Ensure: The LR trade classification function itself returns 3 possibilities:
1, when trade is classified as buyer-initiated;
0, when trade is not classifiable;
-1, when trade is classified as seller-initiated.

```
int LR(double open, double high, double low, double close, double[]closes):
double mid = (high + low)/2
if close > mid then
    return 1
else
    if close < mid then
        return -1
    else
        double pt = close
        for i ← closes.size() − 1 to 0 do
            if pt − closes[i] < 0 then
                return -1
            else
                if pt − closes[i] > 0 then
                    return 1
                end if
                pt = closes[i]
            end if
        end for
        return 0
    end if
end if
```

classification to economic research, the available data generally does not contain this information. As pointed out earlier, the trade direction is not public information on the Warsaw Stock Exchange.

The main aim of this paper was to implement and to compare the QR, TR, LR and EMO trade classification algorithms using high-frequency data for the WSE-listed stocks. The KGH, MCI, and ENP were chosen as the representative Polish companies from three size groups. The empirical experiment shows that the TR and LR procedures perform better on the WSE, while the applicability and accuracy of

Algorithm 4 The EMO trade classification function

Require: *data* - file with the list of transactions from the earliest to the latest; each transaction is written in a separate *line*;
line - string that contains transaction data and must possess following format:
$[Company\_name], 0, [Date : YYYYMMDD], [TimeOfDay : HHMMSS], O, H, L, C, V;$
prevclose - variable that remembers close price of the previous trade; it is set to -1 when a new trading day is to be processed.

Ensure: The EMO trade classification function itself returns 3 possibilities:
1, when trade is classified as buyer-initiated;
0, when trade is not classifiable;
-1, when trade is classified as seller-initiated.

```
int EMO(double open, double high, double low, double close, double prevclose):
if close == low == high then
    return 0
else
    if close == low then
        return 1
    end if
    if close == high then
        return -1
    end if
end if
if prevclose == −1 then
    return 0
end if
if close > prevclose then
    return 1
else
    if close < prevclose then
        return -1
    else
        return 0
    end if
end if
```

the QR and EMO methods is rather low. Moreover, the empirical results turned out to be robust to the choice of the sample and rather do not depend on a firm size.

One of the possible directions for further investigation would be to implement the BVC algorithm [10] and to compare it with the TR and LR procedures, following for example the methodology proposed in [4]. To the best of the authors' knowledge, such research has not been conducted on the WSE thus far.

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PORÓWNANIE WYBRANYCH ALGORYTMÓW KLASYFIKACJI TRANSAKCJI NA GIEŁDZIE PAPIERÓW WARTOŚCIOWYCH W WARSZAWIE S.A.

Streszczenie Badania empiryczne w zakresie mikrostruktury rynku często wymagają wiedzy na temat stron transakcji. Szczególnie ważna jest identyfikacja strony inicjującej transakcję oraz podział na transakcje inicjowane przez nabywcę i sprzedającego. Niestety, większość baz danych intraday nie zawiera takich informacji. Dlatego badacze korzystają z pośrednich metod klasyfikacji. Celem pracy była implementacja i porównanie czterech algorytmów klasyfikacji transakcji na Giełdzie Papierów Wartościowych w Warszawie S.A. Badanie przeprowadzono z wykorzystaniem śróddziennych danych transakcyjnych akcji trzech reprezentatywnych firm, należących do grup spółek dużych (grupa BIG), średnich (grupa MEDIUM) i małych (grupa SMALL). Były to odpowiednio spółki: KGH, MCI oraz ENP. Wszystkie charakteryzują się stosunkowo wysoką płynnością na tle grup, do których należą. Analizy objęły okres od 3 stycznia 2005 do 30 czerwca 2015, z wyróżnieniem trzech jednakowo licznych podokresów: przed kryzysem, kryzys, po kryzysie. Okres globalnego kryzysu finansowego na giełdzie warszawskiej został ustalony w sposób formalny jako przedział czasowy czerwiec 2007-luty 2009.

Słowa kluczowe: algorytmy klasyfikacji transakcji, dane intraday, polski rynek kapitałowy

Artykuł zrealizowano w ramach pracy badawczej S/WI/1/2014.