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A Dynamic Level Technical Indicator Model for Oil Price Forecasting

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A Dynamic Level Technical Indicator Model for Oil Price Forecasting

David Ademola Oyemade [α] & David Enebeli [σ]

Abstract- Investment in commodities and stock requires a nearly accurate prediction of price to make profit and to prevent losses. Technical indicators are usually employed on the software platforms for commodities and stock for such price prediction and forecasting. However, many of the available and popular technical indicators have proved unprofitable and disappointing to investors, often resulting not only in ordinary losses but in total loss of investment capital. We propose a dynamic level technical indicator model for the forecasting of commodities' prices. The proposed model creates dynamic price supports and resistances levels in different time frames of the price chart using a novel algorithm and employs them for price forecasting. In this study, the proposed model was applied to predict the prices of the United Kingdom (UK) Oil. It was compared with the combination of two popular and widely accepted technical indicators, the Moving Average Convergence and Divergence (MACD) and Stochastic Oscillator. The results showed that the proposed dynamic level technical indicator model outperformed MACD and Stochastic Oscillator in terms of profit.

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I. Introduction

The price of oil affects the global economy and geographical events, making oil price uncertain and unstable, because oil is a major source of energy [28]. In the application of computer science and time series mathematical theories to the oil and gas industries , the prediction of oil prices is still a challenge because oil falls under the categories of commodities which are easily affected by change in government policies and unpredictable natural or unnatural events. The oil market is complicated because, like the stock market, its features are neither linear nor stationary [3][4]. Oil, an already volatile market, reached a flash point in 2020 accentuated by the coronavirus (COVID 19) pandemic which resulted in a sharp drop of price that affected the oil exporting countries. Fig. 1 is a pictorial view of an instance in the sharp drop in global oil prices as a result of the COVID 19 pandemic. Fig. 1 shows that oil collapsed to the lowest price in 18 years. Such a price drop negatively impacted on the economy of the nations that depend on oil as a major part of their gross domestic product (GDP) and nations that depend on oil for economy sustenance and survival. Such inadvertent and sharp drops in oil prices also have adverse effects on the performance of software systems designed for the forecasting of oil prices. Therefore, developing a proactive model capable of automation for the prediction of oil prices is of high significance and is worth the efforts.

Fig. 1: Price developments of crude oil in US dollars, from 2000 until April 2020

Technical indicators, most of which adopt time series or deep learning solutions, are suitable for the prediction of oil prices [1] [5] [10] [11] [12]. However,

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many of the available and popular technical indicators have proved unprofitable and disappointing to investors, often resulting not only in ordinary losses but in total loss of investment capital, in spite of the claims of their designers and developers. In this paper, a dynamic level technical indicator model for the forecasting of commodities' prices is proposed. The remaining part of this paper is organized as follows the next section is the background of study. This is, followed by the review of related works, the methodology and the implementation. Finally, the results and discussion are presented and followed by the conclusion and future works.

II. Background of Study

Technical Indicators are primarily intended for displaying some graphical signals on a security charts for the purpose of guiding traders and users on appropriate trading decisions. These graphical signals are displayed through some calculated dependencies achievable through programming codes in a programming language suitable for the terminal employed for the security or commodity. Traditionally, buffers are required in the development of technical indicators because by design, values of indicator arrays must be passed via exchange buffers to a client terminal. Various types of lines and sometimes symbols are usually drawn by the technical indicators. One indicator array and one buffer array are associated with one indicator line, with each buffer having its own index which starts from zero. Fig. 2 demonstrates how values of indicator arrays are passed via a buffer to a client terminal.

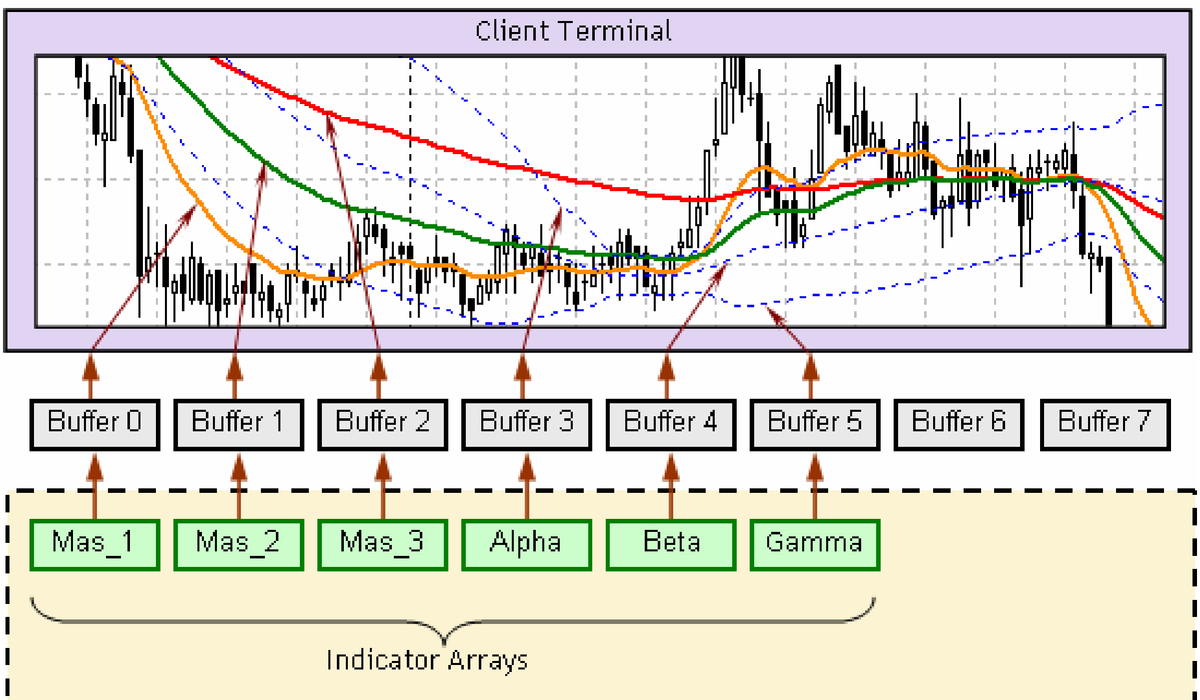

Fig. 2: Technical Indicator Creation - Passing values of indicator arrays via a buffer to a client terminal [13]

Technical analysis refers to the use of technical indicators and historical data for trading decisions in contrast to the use of economic, political or geographical events [3]. The use of events for trading decisions is referred to as fundamental analysis. Technical analysis is a set of rules or charting that anticipates future prices based on the study of the basic security information such as open price, selling price, volume traded, amongst other information. Contemporary technical indicators can be classified into: Trend, Oscillators, Volumes and Bill Williams. Various technical indicators which fall under each can be seen in Fig. 3 which shows the technical indicators tree. Examples of such technical indicators include: Average Directional Movement Index, Bollinger Bands, Average True Range, Bears Power, Accumulative/ Distribution, Money Flow Index, Accelerator oscillator and Alligator.

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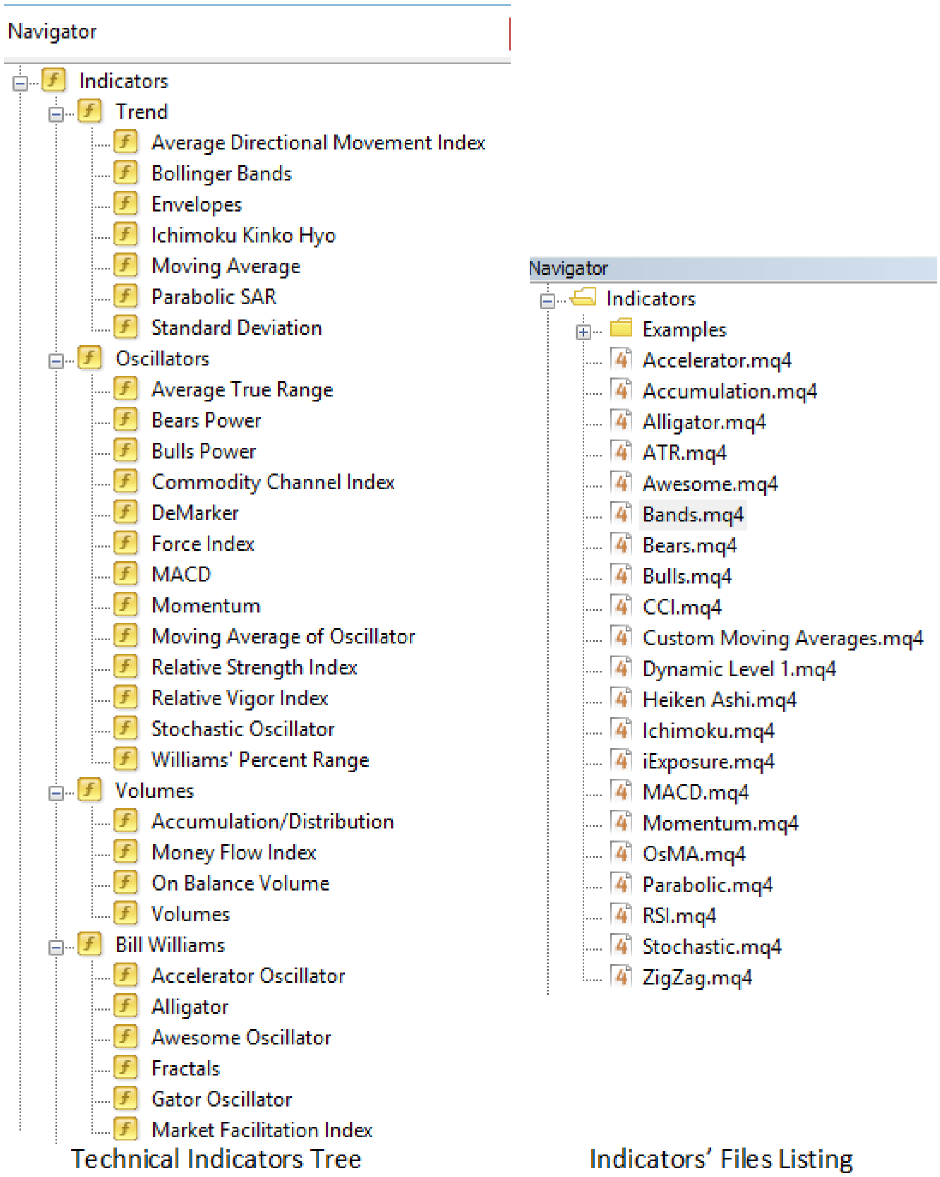

Fig. 3: A Technical Indicators Tree (Showing their Classification) and Indicators' Files Listing

III. Related Works

Although many technical indicators exist, only few are documented publicly in the research community. Previous works relating to technical indicators are discussed in this section. Bartolucci et al [2] proposed a generalized version of moving average convergence and divergence by adopting the martingale and applied the indicator for the monitoring of crude oil prices. Nazário et al [3] gave the classification of technical analysis on stock market in a literature review. Using the combination of technical indicators and news articles as inputs, Vargas et al [5] applied deep learning for the prediction of daily directional stock price movement. They compared the performance of a hybrid model composed of a Convolutional Neural Network (CNN) for the financial news with Long Short-Term Memory (LSTM) for technical indicators. Chan and Teong [6] applied neural networks to enhance technical analysis positing that false breakout had been previously experienced with the use of technical analysis. Oriani and Coelho [7] evaluated the impact of a number of technical indicators on the stock market using multilayer perceptrons (MLP) but presented no model. Gholamiangonabadi et al [14] combined Principal Component Analysis, Stepwise Regression Analysis and Artificial Neural Networks for the performance evaluation of the technical indicators of an electrical industry stock exchange. Thawornwong et al [17] also focused on the application of neural networks for decision making in the stock market. Stanković [15] investigated the effectiveness of least square support vector machine and some traditional technical indicators such as MACD and Relative Strength Index (RSI) for financial series stock trend prediction and investment strategy optimization. Chong and Ng [18] simply tested and compared MACD with RSI using the Financial Times – Institute of Actuaries 30 (FT30) index of Mills. Rosillo [19] also simply tested the RSI, MACD, momentum and stochastic rules for technical analysis using the Spanish stock market. Almeida et al [16] analyzed some technical indicators using an algorithm based on differential evolution to generate Pareto fronts for each technical indicator to achieve multi-objective optimization. Chi and Peng [20] studied the relationship among various technical indicators and using self-organizing map and fuzzy neural network. On the prediction of oil prices, the diverse approaches proposed by other members of the research community include: the use of sentiment on news article [21], autoregressive integrated moving average (ARIMA) model [22], a hybrid of wavelet or Commodity Futures Prices and artificial neural networks [23] [25], deep learning based models [24], statistical learning method [26], time-varying approach [27], gray wave forecasting method and optimization via bagging ensemble models [29].

Most of the existing technical indicator models adopt the statistical approach while recent ones adopt deep learning methodology and they are limited in the diversity of application. Our proposed model creates programmable dynamic levels for price supports and resistances. The proposed model can be used both for trending and hedging markets. In addition, while most of the existing technical indicators were used for stock decision making, our proposed model focuses on the prediction of oil prices. These are some of the main contributions and novelty of this paper.

IV. Methodology

The proposed model leverages on the overriding impact of support and resistance levels of the terminal charts and their effects on the system's profit. An algorithm was developed to capture, establish and indicate the support and resistance for different timeframes of the terminal charts and to dynamically move these levels as the price of the commodity changes. The relative movements of one minute (M1), five minutes (M5), fifteen minutes (M15), one hour (H1), four hour (H4) and daily (D1) timeframes during price trending, reversal and breakout were observed and studied over a period of time. The result of the research observation was then recommended for order placements and other trading decisions.

a) *The Dynamic Level Technical Indicator Model*

The proposed dynamic level technical indicator model consists of three components: the dynamic level component, the graphical component and the traditional technical indicator component. These three components are synchronized and they complement each other in functionality. The composition and operations of the components are explained in this section. The conceptual diagram of the dynamic level technical indicator model is shown in Fig. 4.

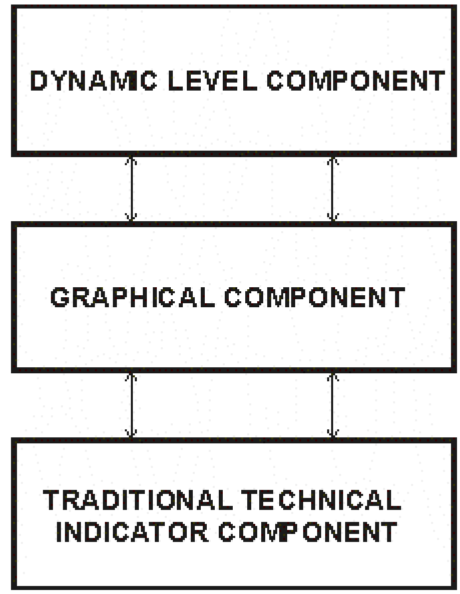

Fig. 4: The Conceptual Diagram of Dynamic Level Technical Indicator Model

b) *The Dynamic Level Component*

The Dynamic Level Component uses the array data structure to store the prices of the upper and lower shadow of price candles for various timeframes. Different array sizes were applied to different timeframes. Different colors were also assigned to the indicator lines as appropriate. Support and resistance levels are determined by the index of the array with highest upper shadow for bullish (or buy) candles and lowest lower shadow for bearish (or sell) candle. The continually changing values of the indexes of upper and lower candle shadows ensure the dynamism of the established support and resistance levels. The algorithm for the dynamic level component is given below. The algorithm defines the procedure TradeLevel_BuyHigh and the procedure TradeLevel_SellLow with some parameters. This procedures can be reused for different time frames.

i. *Algorithm for the Dynamic Level Component*

```
// At Resistances
TradeLevel_BuyHigh(BuyPriceArray[],MaxBuyPriceHighIdx, ActiveArraySize, PeriodFrame)
 {
 MaxBuyPriceHigh; //declaration
  for(int tkk=1;tkk<=ActiveArraySize;tkk++) // inspect the arrays of the selected candles
   {
   if(iClose(Symbol(),PeriodFrame,tkk)>=iOpen(Symbol(),PeriodFrame,tkk)) // if it is a buy pip
     {
     BuyPriceArray[tkk] ←iHigh(Symbol(),PeriodFrame,tkk); // store the upper shadow high prices in the array
     }
   }
  MaxBuyPriceHighIdx←ArrayMaximum(BuyPriceArray,ActiveArraySize,1); // determine the index of the maximum upper shadow high price
  MaxBuyPriceHigh] ←BuyPriceArray[MaxBuyPriceHighIdx]; // store the maxinum upper shadow price as the level
  return (MaxBuyPriceHigh);
 }

// Below is the procedure call at M15 Resistance
MaxBuyPriceHigh15M←TradeLevel_BuyHigh(BuyPriceHigh15M, MaxBuyPriceHigh15MIdx, Active15MArraySize, PERIOD_M15);

// At Support
 TradeLevel_SellLow(SellPriceArray[],SellSelectedPriceArray[],MinSellPriceLowIdx, ActiveArraySize, PeriodFrame)
 {
 MinSellPriceLow;.//declaration
  SellNonZeroCount=1;
  for(int tjj=1;tjj<=ActiveArraySize;tjj++) // inspect the arrays of the selected candles
   {
   if(iClose(Symbol(),PeriodFrame,tjj)<iOpen(Symbol(),PeriodFrame,tjj)) // if it is a sell pip
     {
     SellPriceArray[tjj] ←iLow(Symbol(),PeriodFrame,tjj); // store the upper shadow high prices in the array
     if(SellPriceArray[tjj]>0) //select only positive value and don't include 0
       {
       SellSelectedPriceArray[SellNonZeroCount]=SellPriceArray[tjj];
       SellNonZeroCount←SellNonZeroCount+1;
       }
     }
   }

 MinSellPriceLowIdx←ArrayMinimum(SellSelectedPriceArray,SellNonZeroCount-1,1);
MinSellPriceLow←SellSelectedPriceArray[MinSellPriceLowIdx];
  return (MinSellPriceLow);
 }

// Below is the procedure call at M15 Support
MinSellPriceLow15M ← TradeLevel_SellLow(SellPriceLow15M, SellSelectedPriceLow15M, MinSellPriceLow15MIdx, Active15MArraySize, PERIOD_M15);
```

c) *Traditional Technical Indicator Component*

The traditional technical indicator component uses buffers as explained in section 2. For every line displayed in a traditional technical indicator, a buffer is needed. The algorithm for the traditional technical indicator component at M15 resistance is given below.

i. *Algorithm for Traditional Technical Indicator Component*

```
Declare the array MaxBuyPriceHigh15MBuffer[] for the indicator buffer array
Declare the array MaxBuyPriceHigh15MBuffer[] for the price at resistance
SetIndexBuffer(6,MaxBuyPriceHigh15MBuffer) //initialize the buffer array
  Counted_bars←IndicatorCounted(); // Number of counted bars
  i←Bars-Counted_bars-1;          // Index of the first uncounted
  while(i>=0)                    // Loop for uncounted bars
   {
```

```
MaxBuyPriceHigh15MBuffer[i] ←MaxBuyPriceHigh15M;
i--;                    // Calculating index of the next bar
}
```

d) The Graphical Component

The graphical component displays the various indicators with different object properties. This component sets the line color, width and style. While the changing values of the dynamic levels can be captured with program codes for auto-trading, manual trading depending on the positioning of the indicator lines for trading decision. The algorithm of the graphical component is shown below.

i. *Algorithm for the graphical component*

The algorithm of the graphical component of the dynamic level component given below for M15 resistance

```
for(int b=0; b<2; b+=2)
 {
  ObjectDelete("LineNameLabel"+b);
  ObjectCreate("LineNameLabel"+b,OBJ_HLINE,0,0,MaxBuyPriceHigh15M); //MaxBuyPriceClose1H
  ObjectSet("LineNameLabel"+b,OBJPROP_COLOR,Aqua);
  ObjectSet("LineNameLabel"+b,OBJPROP_WIDTH,2);
  ObjectSet("LineNameLabel"+b,OBJPROP_RAY,False);
 }
```

The algorithm of the graphical component of the traditional technical indicator is given below for M15 resistance.

```
//--- plot MaxBuyPriceHigh15M
 indicator_label  "MaxBuyPriceHigh15M"
 indicator_type   DRAW_LINE
indicator_color  clrAqua
indicator_style  STYLE_SOLID
 indicator_width  2
```

e) Research Observations and Model applications

It was observed in the course of this study that trending in the bullish direction occurs when the M5 line moves above the M15 line or the M15 line moves above the H1 line at the resistance level. Similarly, trending in the bearish direction occurs when the M5 line moves below the M15 line or the M15 line moves below the H1 line at the support level. Price breakout in the bullish direction occurs when the M15 line moves above the H4 line at the resistance level. In the same way, price breakout in the bearish direction occurs when the M15 line moves below the H4 line at the resistance level. These observations, which has not been stated in previous studies by the research community, produced positive results when implemented. They therefore, form part of the contribution to knowledge of this paper.

f) Materials

The experiments carried out in this study were performed with Meta Quote programming language installed on Intel(R) Core(TM) i3-2330M CPU @ 2.20GHz, 4 GB RAM, 64-bit Windows 8 operating system. The program was run on MetaTrader 4 terminal installed on a US based virtual private server.

V. Implementation

The proposed model was implemented for M5, M15, H1, H4 and D1 timeframes. The various properties of the indicator lines in the different timeframes implemented are shown in Table 1. The values of the dynamic level active array size, the line variable names at supports and resistances as well as the line color, line type and line width are shown in Table 1. Fig. 5 illustrates how the proposed model captured the exact support of the H4 with orange color, displayed using the H4 timeframe chart. The proposed technical indicator is implemented with the name "Dynamic Level 1" as shown in Fig. 5. The file name used for saving the indicator's program codes is displayed as "Dynamic Level 1.mq4" under indicators files' Listing in Fig. 3.

Table 1: Dynamic Level Technical Indicators Line Properties

Timeframe	Dynamic Level Active Array Size	Object Property Color	Object Type	Object Width	Line Variable Name at Support	Line Variable Name at Resistance
M1	4		OBJ_HLINE	2		
M5	5	LawnGreen	OBJ_HLINE	2	MinSellPriceLow5M	MaxBuyPriceHigh5M
M15	60	Aqua	OBJ_HLINE	2	MinSellPriceLow15M	MaxBuyPriceHigh15M
H1	72	Yellow	OBJ_HLINE	2	MinSellPriceLow1H	MaxBuyPriceHigh1H
H4	126	Orange	OBJ_HLINE	2	MinSellPriceLow4H	MaxBuyPriceHigh4H
D1	300	Violet	OBJ_HLINE	2	MinSellPriceLowD1	MaxBuyPriceHighD1

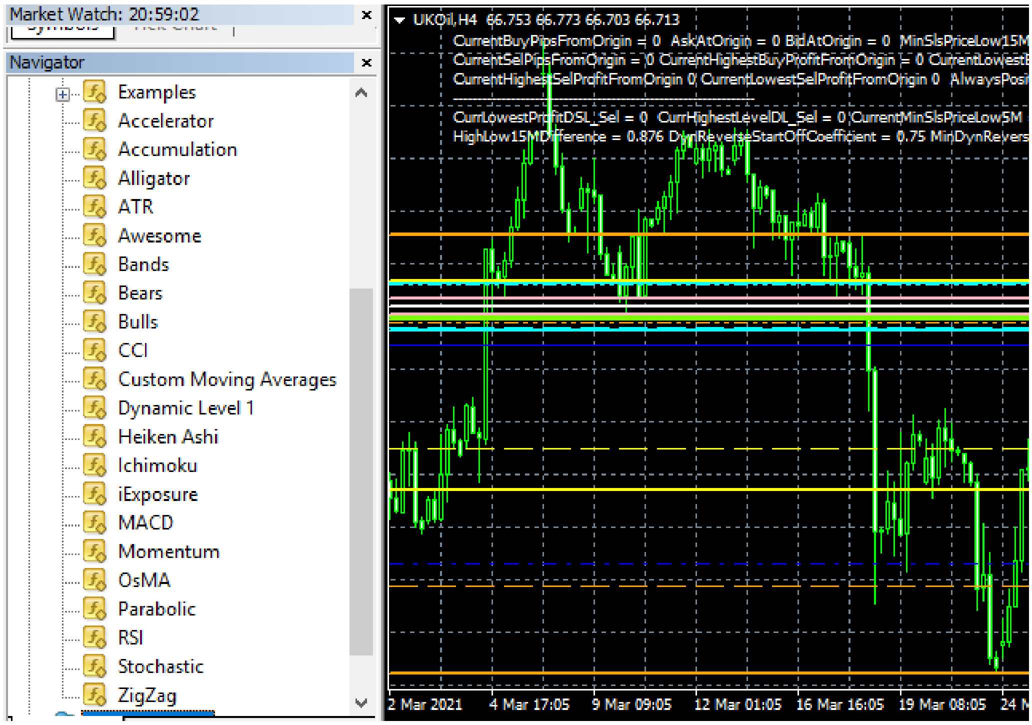

Fig. 5: Dynamic Level Technical Indicator on UK Oil H4 Chart and the Indicators File Listing

VI. Results and Discussion

Two variations of the proposed dynamic level technical indicator were tested. The first is the dynamic level technical indicator 1 which was designed without any form of modification. This was tested on a live trading platform for a period of 3 months to predict the UK Oil prices and compared with the combination of Moving Average Convergence and Divergence and stochastic oscillator which are popularly and widely accepted technical indicators. The results are displayed in Fig. 6. Our proposed model accrued a profit of 315 pips while the MACD/Stochastic technical indicator model accrued a profit of 123 pips. The results shows that our proposed dynamic level technical indicator model is more profitable than the MACD/Stochastic technical indicators. However, it was noticed that good profitable opportunities were lost due to a long period of inactive trading, as a result of unclosed orders. This drawback was addressed in the second technical indicator. In dynamic level technical indicator 2, active profit modification was applied. The result showed that the dynamic level technical indicator 2 outperformed both the dynamic level technical indicator 1 and the MACD/Stochastic indicators by recording 432 pips profit as shown in Fig. 7.

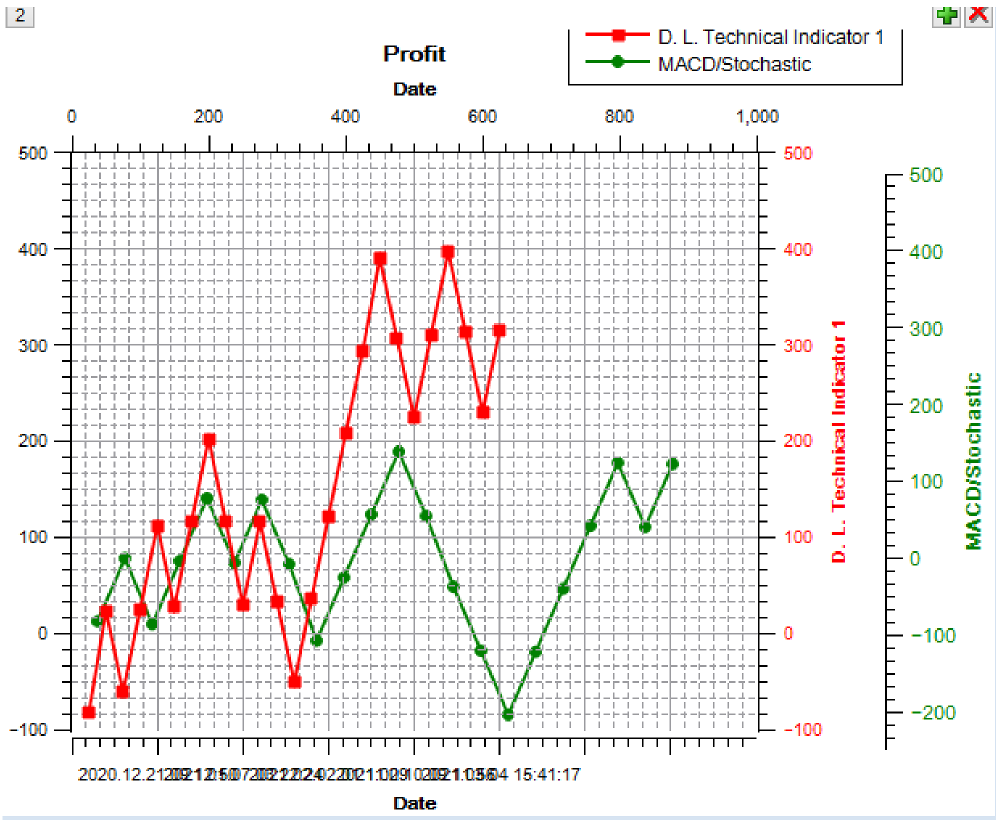

Fig. 6: Three Months Performance Chart of Dynamic Level Technical Indicator 1 and MACD/Stochastic Indicator

An instance of the operation and result of dynamic level technical indicator 2 is shown in Fig. 8 which accentuates the profitability of the proposed model.

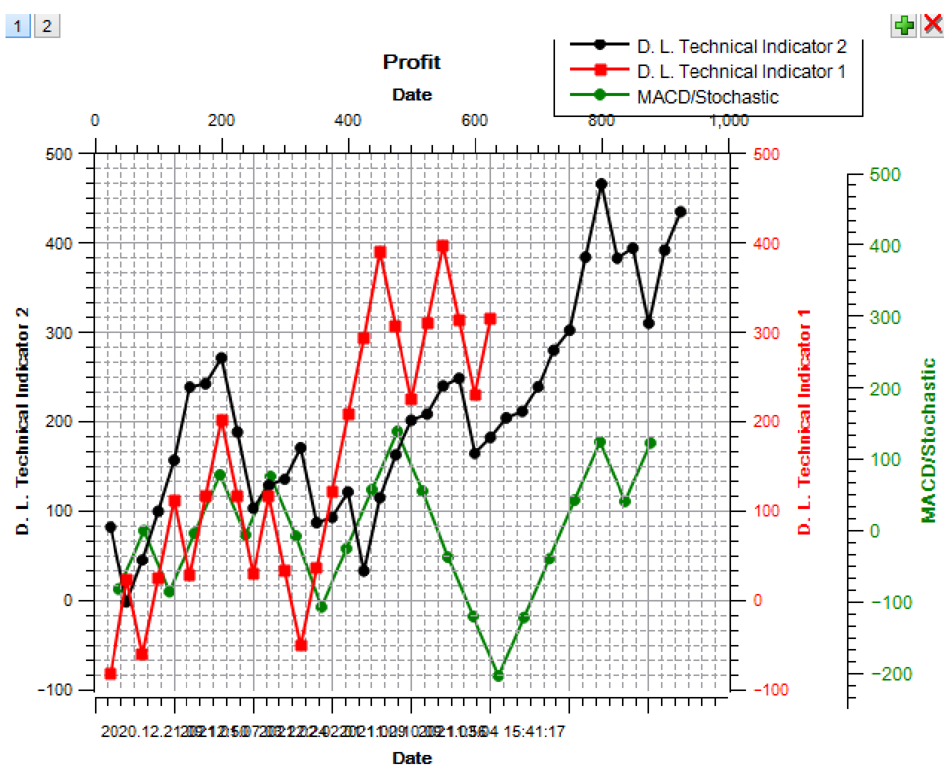

Fig. 7: Three Months Performance Chart of Dynamic Level Technical Indicator 1 and 2 versus MACD/ Stochastic Indicators

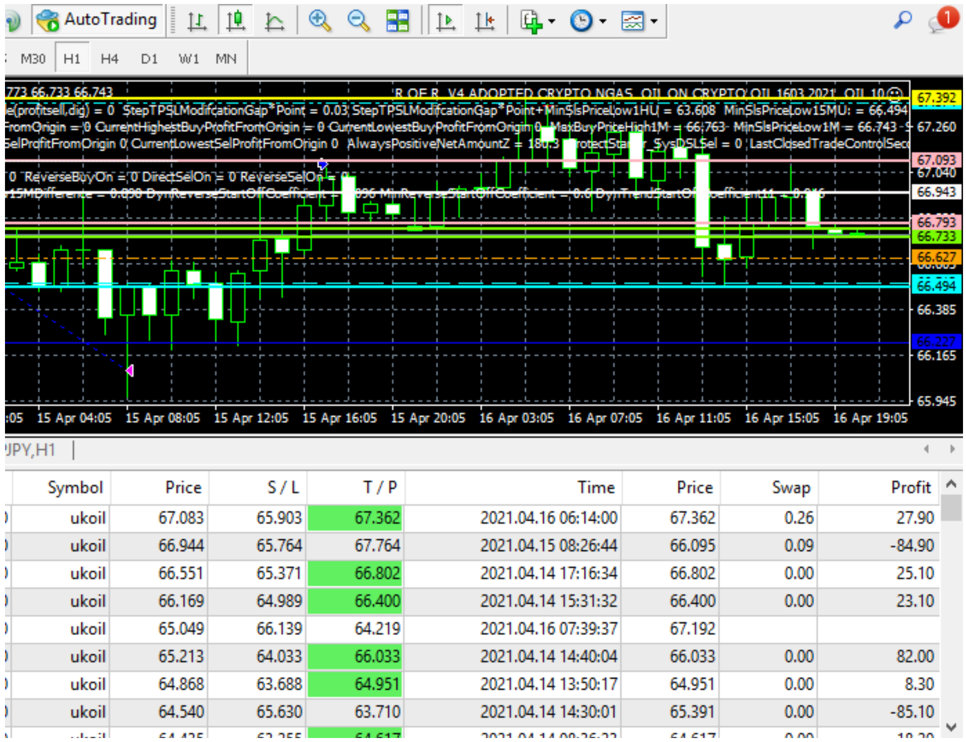

Fig. 8: An Instance of UK Oil Implementation of Dynamic Level Technical Indicator Model

VII. Conclusion and Future Work

The price of oil affects the global economy because oil is a major source of energy. However, the features of the oil market is neither linear nor stationary, making the prediction of oil price a challenge. In this paper, a dynamic level indicator model has been proposed for the forecasting of oil prices. The proposed model was deployed for the UK Oil on live trading for a period of three months and compared with MACD/ Stochastic Oscillator technical indicators which ran at the same period. The result showed that the proposed model is more profitable than MACD/Stochastic Oscillator indicators and therefore can be adopted for oil price prediction. In addition, the research observation of this paper introduces a novel method of price trend prediction based on the relative movements of the dynamic levels in the terminal charts.

Future works shall focus on the investigation of further possible profit optimization of the dynamic level technical indicator model.

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