ICIC Express Letters
Part B: Applications
Volume **10**, Number **10**, October **2019**

ICIC International ©2019 ISSN 2185-2766
pp. 859–866

MINING FUZZY TIME INTERVALS OF FUZZY STOCK PRICE CO-MOVEMENTS PATTERNS

Imam Mukhlash[1], Mohammad Iqbal[1,2], Maya Nurlita Wulandari[1] and Andi Asrafiani Arafah[3]

[1]Department of Mathematics
Institut Teknologi Sepuluh Nopember
Sukolilo, Surabaya, East Java 60111, Indonesia
{ imamm; iqbal }@matematika.its.ac.id; mayanurlitaw@gmail.com

[2]Department of Computer Science and Information Engineering
National Taiwan University of Science and Technology
No. 43, Keelung Rd., Sec. 4, Da'an Dist., Taipei 10607, Taiwan
d10415803@mail.ntust.edu.tw

[3]Faculty of Sport Science
Universitas Negeri Makassar
Jl. A. P. Pettarani, Tidung, Rappocini, Makassar, South Sulawesi 90222, Indonesia
asrafianiarafah@gmail.com

Received April 2019; accepted July 2019

Abstract. *This study presents a fuzzy time interval of fuzzy stock price co-movement pattern, so-called FTI-FSPCM pattern. The FTI-FSPCM is a subsequence which frequently occurs on the historical stock price sequences and comprises fuzzy stock price movement types with fuzzy time intervals. To mine the FTI-FSPCM patterns, we employ FP-GROWTH PREFIX-SPAN algorithm by focusing on stock price discretization based on the fuzzy-linguistic terms. More specifically, the discretization combines the fuzzy return types and the fuzzy time intervals. This study aims to build an investment portfolio for the investor based on the FTI-FSPCM patterns in general, for each company and inter-companies. The experimental results showed that FTI-FSPCM patterns interpret the movements of stock price trends. Furthermore, the FTI-FSPCM patterns can be used as investment decision supports.*
Keywords: Fuzzy stock co-movement, Fuzzy time interval, Mining sequential patterns

1. **Introduction.** Stock as an indication of company assets is a well-known instrument in financial marketing. A company shares its stock price information in order to attract their prospective investors. Definitely, the investors need to analyze the stock price trends on their desired company and/or even curious about how the correlation between the competitors before they decide to invest. When both sides meet with the agreement, the investors hold a stock as their asset warrants in certain company or incorporated companies. In other words, they legally have rights to claim the profit and assets of the company and rightful to attend the General Shareholders Meeting[1].

Predicting the stock price is one promising task on investment decision making. There are many machine learning techniques that have been conducted on it, such as linear regression [1], and support vector regression (SVR) [2]. However, the prediction results do not provide simple visualization for beginner investor to understand or the investors require to hire experts to interpret it. In this case, some researchers studied to visualize the stock price trends using data mining techniques as mining association rules [3]

DOI: 10.24507/icicelb.10.10.859
[1]Online page (accessed on January 7, 2016): http://www.Idx.co.id/id-id/beranda/informasi/bagiinvestor/saham.aspx

and mining sequential patterns [4]. The one challenging task on the mining process is to determine categorical values of continuous values. Categorical values could make the generated association rules or the generated sequence patterns of stock price movements more understandable. A clustering method [5] is a common approach to categorize continuous values, but we need to define the k-number of center points and evaluate it until it reaches the best results. In another way, a fuzzy approach [6] can be utilized to build linguistic terms as the categorical values. By only extracting the association on stock price trends, we may lose the detail of its movements for particular events. Therefore, this study employs mining sequential pattern techniques using FP-GROWTH PREFIX-SPAN algorithm. The FP-GROWTH PREFIX-SPAN performs faster than other predecessor algorithms, such as GSP, FreeSpan or SPADE as the pseudoprojection method can reduce the number and size of the projected databases [7].

This study mines a fuzzy time interval of fuzzy stock price co-movement patterns called FTI-FSPCM patterns. The FTI-FSPCM is a subsequence which frequently occurs on the historical stock price sequences and comprises fuzzy stock price movement types with fuzzy time intervals. We define the stock price movements based on its returns, i.e., profit and loss which are extended into three intervals using fuzzy triangular membership function for each return. Moreover, we also use the fuzzy triangular membership function to denote the time intervals. For an instance, company A has an FTI-FSPCM pattern, i.e., `Profit` is `High` for `Short` time and `Loss` is `High` for `Long` time. Based on the example, we prefer to do not invest on company A. The goal of this study is to present investment guidance for the investors through the generated FTI-FSPCM patterns which explain the stock price trends time period.

To achieve our goals, we first build the FTI-FSPCM patterns in general to represent the whole historical stock price of many companies in Indonesia. Specifically, we extract the FTI-FSPCM patterns for each company; thus, the investors have information about the condition for each company. At last, we provide the FTI-FSPCM patterns for some intercompany. In this case, the investors have better information about the stock price trends for each company to their competitors or alliances, which makes the investors can have second decisions whether invest on that company or to their competitors or alliances.

This paper is organized as follows. Section 2 describes the related works on mining association rules and sequential patterns, especially on stock price co-movements. Section 3 introduces the definition of FTI-FSPCM patterns and the methodology to mine it. Section 4 discusses the generated FTI-FSPCM patterns. Section 5 concludes this paper and explains the future works.

2. **Related Works.** In data mining, there are two mining techniques, which can be used to deliver useful information to the user, i.e., mining association rules (MAR) and mining sequence patterns (MSP). Both techniques have been applied in many real-world problems, such as weather prediction [8], human activity recognition [9], and financial market analysis [10]. Here, we discuss about stock price analysis with MAR and MSP. Ting *et al.* mined stock patterns from only stock sequence – intra-stock patterns and several stock sequences – inter-stock patterns based on MAR on classification [11]. They did many investigations to obtain a fixed threshold, which is used to determine three distinct items. Liao *et al.* combined MAR and *k-means* to get stock category association [12]. Next, Liao and Chu explored association stock co-movement in between two countries, i.e., Taiwan and China [13]. The dataset on Liao's researches comprised categorical values, which are already fit on MAR.

Furthermore, there are two basic things that we need to focus on mining stock price movements. First, we deal with numerical values. In our previous work in [14], we apply a fuzzy approach to transforming the stock price time series into 6-linguistic terms and a single term to describe idle movements. If we implement a cluster approach as in [15], it is expensive to have several simulations by finding the best k-number of center points. Second, we encounter stock price trends. At this stage, we argue that association stock price can capture the characterization trends as opposed to MAR which is based on a single event transaction. From this point of view, we extend our previous work into mining stock price co-movement patterns called FTI-FSPCM patterns. By adding additional fuzzy time interval information on the patterns, we clearly describe how the profit movements will remain or how much time the company needs to solve its losses. To obtain FTI-FSPCM patterns, we employ FP-GROWTH PREFIX-SPAN [7, 16, 17].

3. **Definitions and Methodology.**

This section defines some terminologies, which are related to FTI-FSPCM patterns. This section discusses our proposed methodology to obtain FTI-FSPCM patterns, which consists of three main steps, that is, transformation, mining sequential pattern and analysis.

3.1. **Definitions.**

Assume that we have a historical stock price database $D = \{(p_i, t_i, s_i)| p_i \in P, t_i \in T, s_i \in S\}$. D contains triple sequences of p_i, t_i and s_i, where $1 \leq i \leq |D|$. p_i is a company identity in a set of company identities $P = \{p_1, p_2, \ldots, p_{|P|}\}$. t_i is a date-time when the stock price is being collected in a set $T = \{t_1, t_2, \ldots, t_{|T|}\}$. $s_i \in \mathbb{R}$ is a stock price time series in a set $S = \{s_1, s_2, \ldots, s_{|S|}\}$. To fit with MSP techniques, we discretize the stock price s_i and the date-time t_i using fuzzy membership functions, especially trapezoidal-shaped membership functions. For stock prices $s_i \in S$, initially we define their *returns* based on Equation (1) as follows:

$$R(s_i) = \frac{s_{i+1} - s_i}{s_i} \tag{1}$$

Based on the *return* values from Equation (1), we split the return values into three *return* types, i.e., $R(s_i) > 0$ or $R_p(s_i)$ means profit, $R(s_i) < 0$ or $R_\ell(s_i)$ means loss and $R(s_i) = 0$ means idle/stable – `Stable(S)`. Next, the two *return* types, i.e., *profit* and *loss*, are categorized into three-linguistic terms, respectively. The membership functions for profit denote in this study as follows.

Definition 3.1. *Given profit values $R_p(s_i) > 0$, we define three linguistic terms,* ***`Profit High`*** *– PH,* ***`Profit Medium`*** *– PM, and* ***`Profit Low`*** *– PL, as follows:*

$$\mu_{PL}(R_p(s_i)) = \begin{cases} 0, & \text{if } R_p(s_i) \leq 5 \\ (6 - R_p(s_i)), & \text{if } 5 < R_p(s_i) < 6 \\ 1, & \text{if } R_p(s_i) \geq 6 \end{cases} \tag{2}$$

$$\mu_{PM}(R_p(s_i)) = \begin{cases} 0, & \text{if } R_p(s_i) \leq 5 \vee R_p(s_i) \geq 19 \\ \dfrac{R_p(s_i) - 5}{7}, & \text{if } 5 < R_p(s_i) \leq 12 \\ \dfrac{12 - R_p(s_i)}{13}, & \text{if } 12 < R_p(s_i) < 19 \end{cases} \tag{3}$$

$$\mu_{PH}(R_p(s_i)) = \begin{cases} 0, & \text{if } R_p(s_i) \leq 18 \\ (R_p(s_i) - 18), & \text{if } 18 < R_p(s_i) < 19 \\ 1, & \text{if } R_p(s_i) \geq 19 \end{cases} \tag{4}$$

The membership functions for loss define in this study, as follows.

Definition 3.2. *Given loss values $R_\ell(s_i) < 0$, we define three linguistic terms,* ***`Loss High`*** *– LH,* ***`Loss Medium`*** *– LM, and* ***`Loss Low`*** *– LL, as follows:*

$$\mu_{LL}(R_\ell(s_i)) = \begin{cases} 0, & \text{if } R_\ell(s_i) \geq -18 \\ (-18 - R_\ell(s_i)), & \text{if } -19 < R_\ell(s_i) < -18 \\ 1, & \text{if } R_\ell(s_i) \leq -19 \end{cases} \tag{5}$$

$$\mu_{LM}(R_\ell(s_i)) = \begin{cases} 0, & \text{if } R_\ell(s_i) \leq -19 \vee R_\ell(s_i) \geq -5 \\ \dfrac{R_\ell(s_i) + 19}{7}, & \text{if } -19 < R_\ell(s_i) \leq -12 \\ \dfrac{-12 - R_\ell(s_i)}{7}, & \text{if } -12 < R_\ell(s_i) < -5 \end{cases} \tag{6}$$

$$\mu_{LH}(R_\ell(s_i)) = \begin{cases} 0, & \text{if } R_\ell(s_i) \leq -6 \\ (R_\ell(s_i) + 6), & \text{if } -6 < R_\ell(s_i) < -5 \\ 1, & \text{if } R_\ell(s_i) \geq -5 \end{cases} \tag{7}$$

From Definition 3.1 and Definition 3.2, we have a set of fuzzy stock price movement distinct items $I_g = \{\mathtt{PH}, \mathtt{PM}, \mathtt{PL}, \mathtt{LH}, \mathtt{LM}, \mathtt{LL}, \mathtt{S}\}$. In addition, we also use trapezoidal-shaped membership function for date-time, and then we have fuzzy time intervals, such as the following.

Definition 3.3. *Given date-time t_i, we define three linguistic terms, `short`, `middle`, and `long`, as follows:*

$$\mu_{short}(t_i) = \begin{cases} 0, & \text{if } t_i \geq 7 \\ \dfrac{7 - t_i}{5}, & \text{if } 2 < t_i < 7 \\ 1, & \text{if } t_i \leq 2 \end{cases} \tag{8}$$

$$\mu_{middle}(t_i) = \begin{cases} 0, & \text{if } t_i \leq 2 \vee t_i \geq 28 \\ \dfrac{t_i - 2}{13}, & \text{if } 2 < t_i \leq 15 \\ \dfrac{28 - t_i}{13}, & \text{if } 15 < t_i < 28 \end{cases} \tag{9}$$

$$\mu_{long}(t_i) = \begin{cases} 0, & \text{if } t_i \leq 15 \\ \dfrac{t_i - 15}{13}, & \text{if } 15 < t_i < 28 \\ 1, & \text{if } t_i \geq 28 \end{cases} \tag{10}$$

From Definition 3.3, we have a set of fuzzy time intervals $I_f = \{\mathtt{short}, \mathtt{middle}, \mathtt{long}\}$. We now build two sets based id-companies, such that a set of fuzzy stock price co-movements (FSPCM) sequences and a set of FTI-FSPCM sequences. $G = \{\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_{|P|}\}$ is a set of FSPCM sequences, where $\mathbf{g}_j = \big((g_{j_1}, t_{j_1}), (g_{j_2}, t_{j_2}), \ldots, (g_{j_n}, t_{j_n})\big)$ and $g_{j_k} \in I_g$. $F = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_{|P|}\}$ is a set of FTI-FSPCM sequences, where $\mathbf{f}_j = \big((f_{j_1}, \ell_{j_1}), (f_{j_2}, \ell_{j_2}), \ldots, (f_{j_m}, \ell_{j_m})\big)$, $f_{j_k} \in I_g$ and $\ell_{j_k} \in I_f$. Next, we give a description about a membership degree of $\mathbf{g}_j$ and $\mathbf{f}_j$ below.

Definition 3.4. *Given two sequences $\mathbf{g} = \big((g_1, t_1), (g_2, t_2), \ldots, (g_n, t_n)\big)$ and $\mathbf{f} = \big((f_1, \ell_1), (f_2, \ell_2), \ldots, (f_m, \ell_m)\big)$, and $f_1 = w_{k,1}, f_2 = w_{k,2}, \ldots, f_m = w_{k,m}$, where $1 \leq w_{k,1} \leq w_{k,2} \leq \cdots \leq w_{k,m} \leq n$, $\mathbf{f}$ is a subset of fuzzy time interval of $\mathbf{g}$ with membership degree γ by satisfying the following conditions:*

$$t_{w_{k,j}} = t_{w_{k,j+1}} - t_{w_{k,j}},\ 1 \leq j \leq m-1 \wedge 1 \leq k \leq K \tag{11}$$

$$\gamma = \max_{1 \leq k \leq K} \min_{1 \leq j \leq m-1} \{\mu_{I_f}(t_{w_{k,j}})\} \tag{12}$$

Assume we have $\mathbf{f}_p$ which is a subsequence of $\mathbf{f}$. To decide whether $\mathbf{f}_p$ is frequent subsequence in F, we denote a relative support value of $\mathbf{f}_p$, as follows.

Definition 3.5. *Given a subsequence* $\mathbf{f}_p$ *and a membership degree* $\gamma(\mathbf{f}_p, \mathbf{g})$, *a relative support value of* $\mathbf{f}_p$ *is given by*

$$supp_G(\mathbf{f}_p) = \sum_{j \in G} \frac{\gamma(\mathbf{f}_p, \mathbf{g}_j)}{|G|} \tag{13}$$

where $|G|$ *is a cardinality of set* G.

Finally, we can define FTI-FSPCM pattern, as follows.

Definition 3.6. *Given a minimum support threshold* α, *we say a subsequence* $\mathbf{f}_p$ *as FTI-FSPCM pattern if and only if* $supp_G(\mathbf{f}_p) \geq \alpha$.

3.2. **Methodology.** To extract FTI-FSPCM patterns, we present a methodology that comprises three main stages: (i) pre-processing stage, (ii) mining sequential patterns stage and (iii) analyzing stage. In the pre-processing stage, a dataset D is cleaned by deleting missing values and transforms it into a set F. For instance, we depict the transformation phase in Figure 1.

After we obtain a set of FTI-FSPCM sequences F, we set the minimum support threshold α and do mining sequential patterns using FP-GROWTH PREFIX-SPAN algorithm.

Time	Company id	Stock price
01-04-2010	1	5.050
01-05-2010	1	5.100
01-06-2010	1	4.950
...	...	...

Company id	FSPCM sequence
1	(PL,01-05-2010),(LH,01-06-2010),...
2	(PL,01-05-2010),(LH,01-06-2010),...
3	(LH,01-05-2010),(LH,01-06-2010),...
...	...

Company id	FTI-FSPCM sequence
1	(PL,short),(LH,short),...
2	(PL,short),(LH,short),...
3	(LH,short),(LH,short),...
...	...

FIGURE 1. An illustration of transformation phases

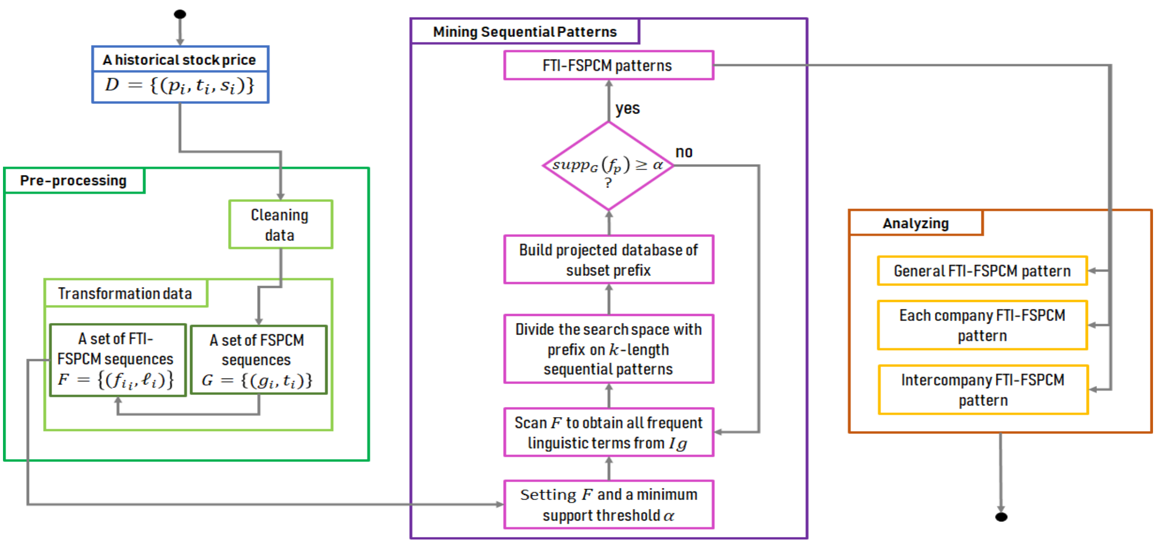

FIGURE 2. A methodology to mine FTI-FSPCM patterns

In the mining process, we scan a set F to get all frequent linguistic terms from I_g. The next step divides the search space with the prefix of k-length sequential patterns. After holding the prefix, we build the projected database based on the subset of the prefix. Then, we check whether the support values are greater than or equal to α to obtain the k-length FTI-FSPCM patterns. Otherwise, we recursively do the same steps until meeting the stopping conditions. There are two stopping conditions, i.e., we cannot find any 1-length sequential patterns and/or all support values of k-length sequential patterns with $k > 1$ are less than α. For the analyzing stage, we generate three kinds of FTI-FSPCM patterns such as general, each company and inter-companies to provide some investment portfolio to the investors.

In the next section, we will discuss the experimental results by specifying several minimum support thresholds α in a range $[0, 1]$ and explain how the generated FTI-FSPCM patterns in general, for each company, and intercompany which can be used as investment portfolio.

4. **Experimental Results.**

4.1. **Dataset information.** We collected a history price of Yahoo Finance data of 63 stock companies in Indonesia that consists of 9 areas, that is, (1) finance, (2) consumer, (3) infrastructure, utilities and transportation, (4) trade, service and investment, (5) construction, property and real estate, (6) basic industry and chemicals, (7) mining, (8) plantation, and (9) industrial. We used closed data per day from January 4, 2010 until December 30, 2015. By pre-processing data, we recorded 97.932 FTI-FSPCM sequences.

4.2. **Analysis of stock price co-movements patterns.** We now discuss the FTI-FSPCM patterns in three kinds as investments portfolio. First, we describe FTI-FSPCM patterns in general by showing the impact of minimum support threholds α on the number of generated FTI-FSPCM patterns. Second, we explain about the FTI-FSPCM patterns for each company. At last, we illustrate the FTI-FSPCM pattern for several inter-companies.

4.2.1. *Analysis of general FTI-FSPCM patterns.* When we generated FTI-FSPCM patterns in general, we investigate that the number of FTI-FSPCM patterns is increased when the values of support threshold α are decreasing. It is depicted in Figure 3.

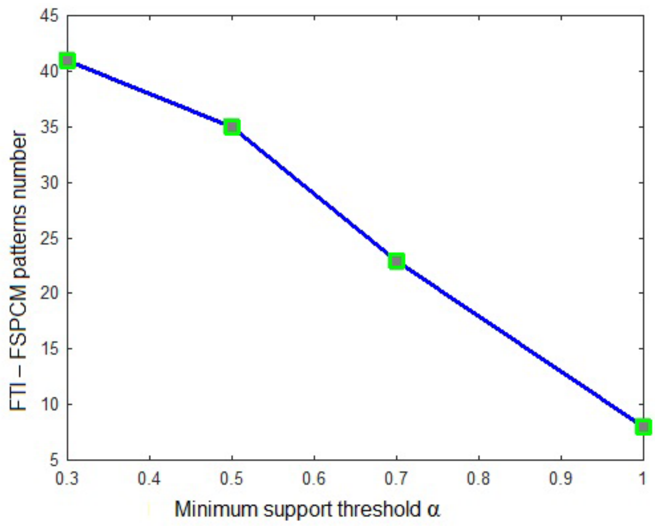

FIGURE 3. A relationship between minimum support thresholds α vs the number of FTI-FSPCM patterns in general

After several observations, we obtain 52 FTI-FSPCM patterns for $\alpha = 0.5$ (see Table 1). For an instance, {`Profit`, `Low`}, `short`, {`Loss`, `Low`}, `short`, {`Stable`} with support value 0.956. At the beginning, a company achieves `Low-Profit` for a `short` period. Then, the company suffers `Low-Loss` in a `short` period. Later, the condition stays remain (i.e., `Stable`). Another pattern is {`Profit`, `Medium`}, `long`, {`Loss`, `Medium`} with the support values 1. It means that the company gets `Medium-Profit` in a `long` period at first. Afterwards, the company suffers `Medium-Low`. According to both patterns, we may have a doubt to invest since the company suffers `Loss` in the end. Furthermore, it happens almost in all companies as the support value is greater than 0.9. However, we still have other FTI-FSPCM patterns to be analyzed in Table 1, and then we can take a decision.

Table 1. General FTI-FSPCM patterns with $\alpha = 0.5$

FTI-FSPCM patterns	Support value
PL	1
LL	1
...	...
PL, short, LL	0.956
PM, long, LM	1
PL, long, PH	1
PM, long, PH	1
...	...
PL, short, LH, short, L, short, L	0.935

4.2.2. *Analysis of FTI-FSPCM patterns of each company.* In this section, we provide FTI-FSPCM patterns for each company. As in the dataset information, we have 63 companies. However, we only show FTI-FSPCM patterns for three companies with support value = 1 due to the limited space.

Table 2. FTI-FSPCM patterns in id-companies p_1, p_3, p_4 with $\alpha = 0.3$

FTI-FSPCM patterns	Support value
p_1_LL, long, p_1_PL, long, p_1_PM	1
p_3_LL, long, p_3_PL, long, p_3_PM	1
...	...
p_4_PH, long, p_4_S, long, p_4_PM	1

During our experiments, we have some FTI-FSPCM patterns that can be considered as bad conditions to invest, e.g., p_1_LL, `long`, p_1_PL, `short`, p_1_LH with support value = 1.

4.2.3. *Analysis of FTI-FSPCM patterns with intercompany relations.* In this part, we present relationship among three companies p_1, p_2, and p_3. We use a minimum support threshold $\alpha = 0.3$ and it is described in Table 3.

Table 3. FTI-FSPCM patterns for inter-company p_1, p_2, and p_3 with $\alpha = 0.3$

FTI-FSPCM patterns	Support value
p_2_PL, long, p_1_PM	1
p_3_LL, long, p_1_PH	1
...	...
p_3_PL, short, p_2_LH, long, p_2_PM	1

Even though we work on generating FTI-FSPCM patterns for intercompany, we found FTI-FSPCM patterns for a single company. It happens in id-company p_1, i.e., the FTI-FSPCM pattern is `p`$_1$`_PL`, `short`, `p`$_1$`_PL`, `short`, `p`$_1$`_S` with the support value being 1. It means that the number of transactions for company p_1 is larger than other companies, in this case p_2 and p_3.

5. **Conclusions.** In this study, we build FTI-FSPCM patterns which are able to interpret the stock price trends by considering two aspects, i.e., *return* types with different levels and time intervals of each *return*. Moreover, we bring three kinds of FTI-FSPCM patterns. In general, we consider the stock price time-series of whole companies, which can be used as initial decisions. Next stage, we make FTI-FSPCM patterns for each company; thus, the investors can decide the most profitable company in the future. After all, we still need to give more information about their relations with other related companies. The relations can be used to describe their transition in the future.

In the future, we will work on employing FTI-FSPCM patterns to predict the stock price in the next day, or even build decision support systems to help the investors get a better understanding.

REFERENCES

[1] Y. E. Cakra and B. D. Trisedya, Stock price prediction using linear regression based on sentiment analysis, *Proc. of ICACSIS*, pp.147-154, 2015.

[2] B. M. Henrique, V. A. Soberio and H. Kimura, Stock price prediction using support vector regression on daily and up to the minute prices, *The Journal of Finance and Data Science*, vol.4, pp.183-201, 2018.

[3] S. H. Liao, P. H. Chu and T. K. Teng, Mining the co-movement in the Taiwan stock funds market, *Expert Systems with Applications*, vol.38, pp.5276-5288, 2011.

[4] H. Li and H. Du, Stock sequence pattern mining method based on SWI-GSP algorithm, *Proc. of DMCIT*, Phuket, Thailand, 2017.

[5] S. Aghabozorgi and Y. W. Teh, Stock market co-movement assessment using a three-phase clustering method, *Expert Systems with Applications*, vol.41, no.4, pp.1301-1314, 2014.

[6] H.-J. Zimmerman, *Fuzzy Set Theory*, 1965.

[7] J. Pei et al., Mining sequential patterns by pattern-growth: The PrefixSpan approach, *IEEE TKDE*, vol.16, pp.1424-1440, 2004.

[8] M. Iqbal, I. Mukhlash and H. M. Astuti, The comparison of CBA algorithm and CBS algorithm for meteorological data classification, *ISICO*, 2013.

[9] I. Mukhlash, D. Yuanda and M. Iqbal, Mining fuzzy time interval periodic patterns in smart home data sensor, *International Journal of Electrical and Computer Engineering*, vol.8, pp.3374-3385, 2018.

[10] S.-H. Liao, P.-H. Chu and Y.-L. You, Mining the co-movement between foreign exchange rates and category stock indexes in the Taiwan financial capital market, *Expert Systems with Applications*, vol.38, no.4, pp.4608-4617, 2011.

[11] J. Ting, T. C. Fu and K. F. L. Chung, Mining of stock data: Intra- and inter-stock pattern associative classification, *Proc. of DMIN*, NV, USA, pp.30-36, 2006.

[12] S.-H. Liao, H.-H. Ho and H.-W. Lin, Mining stock category association and cluster on Taiwan stock market, *Expert Systems with Applications*, vol.35, nos.1-2, pp.19-29, 2008.

[13] S.-H. Liao and P.-H. Chu, Data mining investigation of co-movements on the Taiwan and China stock markets for future investment portfolio, *Expert Systems with Applications*, vol.40, no.5, pp.1542-1554, 2013.

[14] A. A. Arafah and I. Mukhlash, The application of fuzzy association rule on co-movement analyze of Indonesian stock price, *Procedia Computer Science*, vol.59, pp.235-243, 2015.

[15] K.-P. Wu, Y.-P. Wu and H.-M. Lee, Stock trend prediction by using K-means and AprioriAll algorithm for sequential chart pattern mining, *Inf. Sci. Eng.*, vol.30, no.3, pp.653-667, 2014.

[16] Y.-L. Chen, M.-C. Chiang and M.-T. Ko, Discovering time-interval sequential patterns in sequence databases, *Expert Systems with Applications*, vol.25, no.3, pp.343-354, 2003.

[17] I. Mukhlash et al., Mining fuzzy time interval sequential pattern on event log data using FP-Growth-Prefix-Span algorithms, *Proc. of AIP-ICoMPAC*, 2016.