Volume 376, Issue 36

ECBA-2016

December 21-22, 2016

Istanbul, Turkey

CONFERENCE PROCEEDINGS

BOOK OF FULL PAPERS

ECBA-2016

International Conference on
"Engineering & Technology, Computer, Basics & Applied Sciences"
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International Conference on
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(ECBA-2016)
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Proceedings of the International Conference on

"Engineering & Technology, Computer, Basics & Applied Sciences (ECBA-2016)"

ISBN: ***978-969-683-009-3***

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International Conference on "Engineering & Technology, Computer, Basic & Applied Sciences" serves as platform that aims to help the scholarly community across nations to explore the critical role of multidisciplinary innovations for sustainability and growth of human societies. This conference provides opportunity to the academicians, practitioners, scientists, and scholars from across various disciplines to discuss avenues for interdisciplinary innovations and identify effective ways to address the challenges faced by our societies globally. The research ideas and studies that we received for this conference are very promising, unique, and impactful. I believe these studies have the potential to address key challenges in various sub-domains of social sciences and applied sciences.

I am really thankful to our honorable scientific and review committee for spending much of their time in reviewing the papers for this event. I am also thankful to all the participants for being here with us to create an environment of knowledge sharing and learning. We the scholars of this world belong to the elite educated class of this society and we owe a lot to return back to this society. Let's break all the discriminating barriers and get free from all minor affiliations. Let's contribute even a little or single step for betterment of society and welfare of humanity to bring prosperity, peace and harmony in this world. Stay blessed.

Thank you.

Malika Ait Nasser
Conference Chair
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ISBN 978-969-683-009-3

ECBA -16

Numerical Investigation of the Flow Structure around a Cylinder for Different Fluids and Reynold Numbers

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Abstract

In engineering areas, such as chimneys, bridges, nuclear power plants, airplanes, submarines and high buildings are exposed to fluid or gases flows. As we know there is amount of vibrations, loads, vortexes around of bodies which are exposed flows. Also, these undesirable situations are required some solutions. İn this regard for solutions of such that problems, analysis of flow around bodies with regard to velocity distribution, streamlines, vortexes is a significant issue. From this perspective because of its easy geometry, flow around of cylinder has been investigated on account of velocity distribution, streamlines, vortexes for different fluids and Reynold numbers by means of Anysis CFX 14.5. Laminar and steady flow was handled for two different cases. Case 1 and case 2 are differs from each other in term of boundary conditions for related fluids and Reynold numbers. Finally, from results in question vortex zones, velocity and pressure distribution and drag coefficient of both cases are compered for case 1 and case 2.

Keywords— Steady State Flow Around a Cylinder, Laminar Flow Around a Cylinder, Flow Around a Blunt Body, Drag Coefficient

Introduction

Understanding flow structure around blunt bodies is an important phenomenon due to come up with solutions for problems related flow physics. For examples, blunt bodies exposed to air or water flow is pipe lines, risers, submarines, bridges feet, chimneys, airway vehicles etc. Flow structure also can be changed with a lot of variables such as Reynold number, different fluid, velocity structure of flow, boundary conditions, velocity boundary layer, cross flow effect, vicinity of wall near to the blunt body etc. Change in any of these variables will be changed the characteristic of flow effect around body. This study handled to understand different boundary condition effect on flow characteristic over smooth cylinder with respect to wide range different Reynold numbers and different fluids for steady laminar flow. So from results velocity distribution, pressure distribution, wake region vorticity, drag coefficient versus with related Reynold numbers were investigated.

There are a lot of literatures in this theme because there is a lot of variables effect the characteristic of flow over blunt bodies. For example in [1] numerical investigation on three dimensional flow over cylinder was taken into consideration for steady and unsteady state for Reynold number equal to 39000. In study in question firstly steady state handled, then unsteady state handled then two different states were compared with each other. For both states boundary conditions were taken as velocity inlet, pressure outlet, symmetry and periodic interface. For domain dimensions in Cartesian coordinate X, Y, Z was 32D, 16D, 4D respectively. Unsteady state investigated for two different cases, for case 2a the velocity profile taken as u(y) do not uniform but for case 2b uniform velocity boundary condition applied. Wall to the vicinity of the cylinder taken into consideration to understand wall effect on flow characteristic. It was observed that velocity profile for wake region agreement with previous studies. It was observed that for case 2a and case 2b vortex shedding was suppressed. In [2] numerical investigation of unsteady flow around a cylinder was discussed. To observed wake dynamic and flow structure unsteady flow over rotating cylinder taken under microscope in related study. Finally it was observed that circumferential velocity exceeding about two times flow velocity the von-Karman vortex shedding occurred for low rotational speed disappeared. In [3] the modeling of flow around a cylinder and analyzing and swirl control was examined. Controller design has been done for swirl measurement by means of MATLAB based Navier2d. Then for certain conditions analyses has been done. With help of the swirl controller the vortices occurred behind the cylinder have begun to be suppressed by blowing air at the top and bottom of the cylinder. In another study [4] flow around a circular cylinder is investigated by using Abaqus/CFD. In this study CFD analysis accomplished for flow over a circular cylinder exposed to uniform velocity. From results

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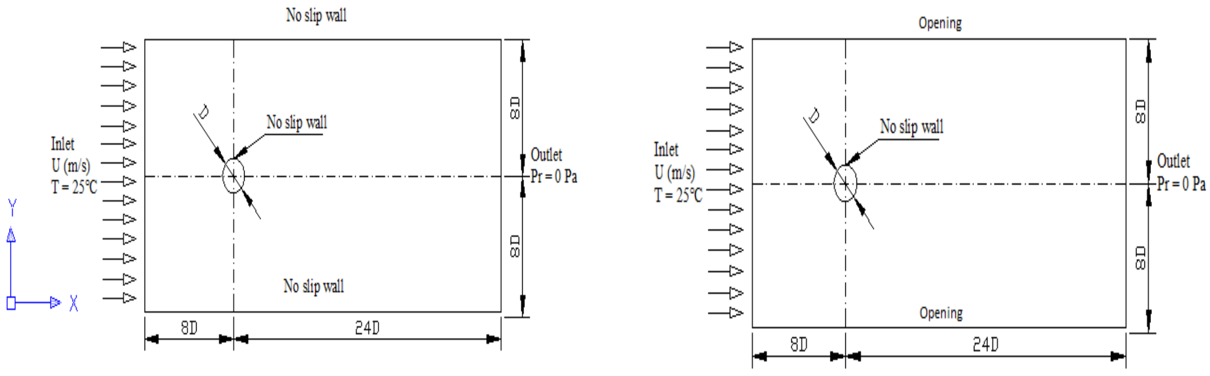
various occurrences point out related with von-Karman vortexes. It was observed that for R >200 transition flow occur from laminar to turbulent and so three dimensional vortexes occurs. As ıt is known drag coefficient most important parameter in respect to flow around blunt bodies. To evaluate drag coefficient in [5] experiments on flow over a circular cylinder accomplished for different cylinder diameters as 12.5mm, 15mm, 25mm and different air velocities. For calculation of drag coefficient two main methods were used which known as direct weighing method and pressure distribution method. Calculated coefficients compared with each other in terms of two methods. Important deviation occurred for two methods. Of course ıt was observed weighing method was higher accurate rate than pressure distribution method

Physical Model and Boundaries

Physical model is represented in Fig 1. For both case. Fig.1a represented case 1, Fig.1b also represented case 2. Case 1 and case 2 differ from one other in term of boundary conditions which illustrated related figures. So the effect of the boundary conditions on the flow was tried to be understood. Model in question is taken into consideration in 3D dimension (X, Y, Z) in dimensionless form. These dimensions were taken as 32D, 16D, 0.25D respectively for both cases. The center of the cylinder is placed 8D away from inlet and 8d away from top and bottom boundaries. In present study cylinder dimension D is equal to 2mm. Also other dimensions were taken as accordance with this magnitude. Doman inlet was taken as uniform velocity distribution and velocity magnitude was calculated accordance with related Reynold number and related fluid properties of course. Temperature of fluid was taken as 25°C for both fluids. As seen from physical model figure at outlet boundary condition relative pressure magnitude was taken as zero Pa. Top and bottom edges were taken as no slip walls and adiabatic walls so shear stress in related region was considered as zero. At front and back edges of channel, symmetry boundary conditions were considered.

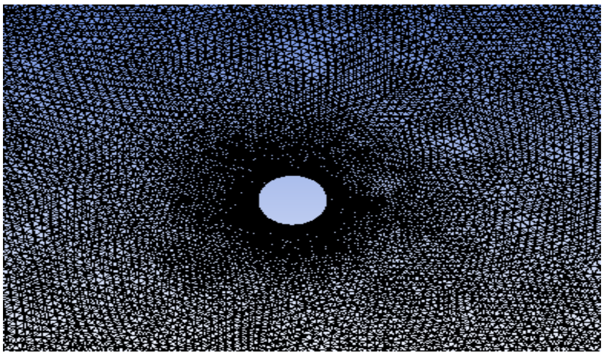


a) b)

Figure 1: Physical model, a) case 1 model, b) case 2 model

Two different fluids were used for flow domain, which consists of air and water.

Mesh configuration and mesh accuracy shown in Fig.2a. and Fig.2b. respectively. Mesh accuracy was proved for related element sizes which demonsrated in Fig.2b. As seen from that figure three different mesh sizes were compared to ensure accuracy in respect to centerline velocity gradient. 345393, 510625, 821171 element sizes were taken into consideration. That is to say for three different mesh sizes accuracy was proved about rate of 100 %. All numerical investigations were handled for element sizes 821171.



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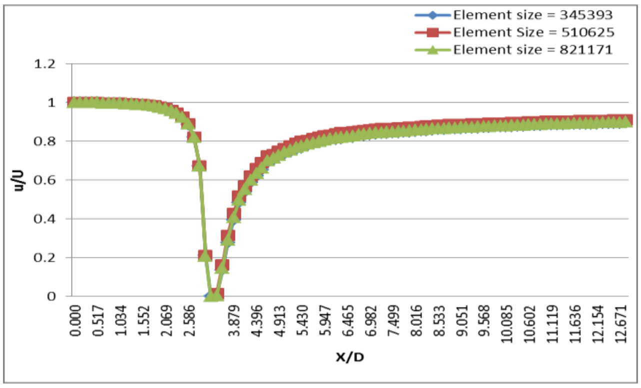


b)

Figure 2: Mesh structure, a) Mesh configuration, b) Mesh accuracy

Mathematical Model and Governing Equations

Numerical simulation done by Anysis CFX solver is based on RANS form of momentum and mass conservation equations. RANS form of momentum and mass conservation equations for incompressible flows using by CFX fluid domain solver with cartesians coordinate system shown in equation (B.1) and (B.2).

$$\rho\left(u_i\frac{\partial u_j}{\partial x_i}\right) = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_i}\left((\mu+\mu_t)\frac{\partial u_j}{\partial x_i}\right) \quad j = 1, 2, 3 \qquad \text{(B.1)}$$

$$\frac{\partial u_i}{\partial x_i} = 0 \qquad \text{(B.2)}$$

To come up with suitable comments related results, drag coefficient must be calculated. As known drag coefficient is depend on drag force magnitude, flow velocity, fluid density, and related area. That is to say it can be formulated like equation (B.3).

$$C_D = F_D/(1/2.d.U^2.A) \qquad \text{(B.3)}$$

Results and Discussions

Velocity Distribution

Fig. 3a. and Fig. 3b. show velocity distribution of case 1 and case 2 respectively. Because of the similarity of velocity distributions for both flow related figures shown for water flow only. As ıt seen for case 1 the wall boundary condition effected the velocity distribution because of boundary layer. As we know when a flow contact with wall, ıts velocity takes ıts zero value at the wall, ıts value increases as farther from wall. Like that from fig.3a wall effect is seen which demonstrated that velocity magnitude change from zero at wall to ıts local value at further region. For low Reynolds Number boundary layer thicker than high Reynold numbers. This indicates that the frictional forces at this Reynold number are more dominant than the inertial forces on the wall. As we know Reynold number refers to the ratio of the inertia forces to the frictional forces. Wall effect observed up to Re 100 for case 1, of course for case 2 there is no wall effect, opening boundary effect can be observed. If the Reynold number is greater than 100 for case 1, the enhanced flow was observed. When Reynold number equal to 200 the velocity distribution of case 1 and case 2 are close to each other (Fig.3a and Fig. 3b). Velocity distribution of case 2 takes ıts enhanced form nearly at Reynold number equal to 100. That is to say at case 2 flow take its enhanced form for lower.

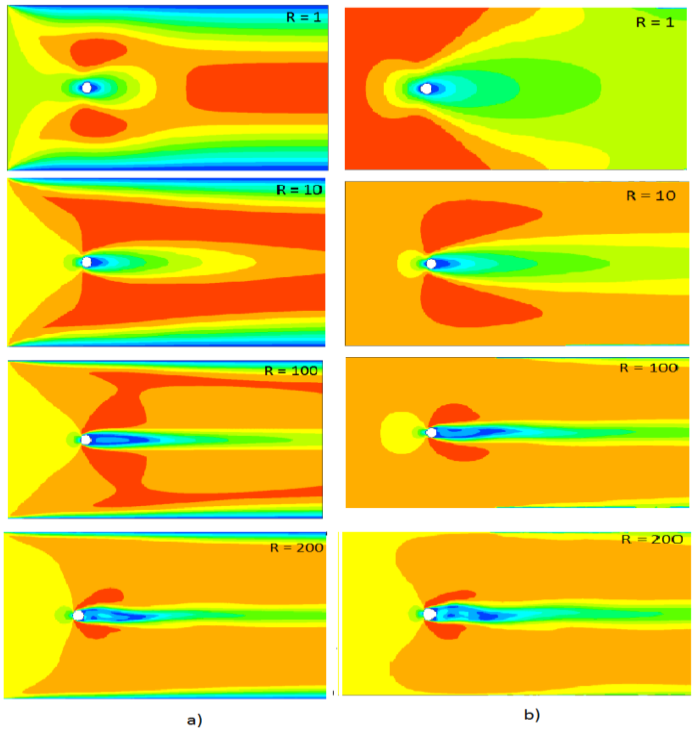


Figure 3: Velocity distribution of water flow a) Case 1, b) Case 2

Reynold number then case 1 due to the wall effect. A significant point is that for case 1 velocity magnitude change from inlet to outlet because of viscous effect of wall boundary condition, but there is no significant change velocity distribution in case 2 due to the opening boundary condition. Another important situation is that for both cases velocity magnitude change due to solid cylinder wall effect.

Static pressure distribution shown at Fig. 4a and Fig. 4b indicated case1 and case 2 respectively. Pressure distribution shown for water only, because of similarity was observed for both flows. From pressure and velocity figures mainly ıt can be said that because of the pressure increase in front of the cylinder the velocity inclined to decreases. Especially for low Reynolds number e.g. for Reynold equal to 1 and 10 stagnation zone occur and ıt cause the velocity to fall to zero. At rear side of cylinder due to the flow separation and vorticity, pressure increases, so velocity decreases. This situation can be observed almost for all Reynold numbers in both cases. Velocity distribution differ from one another especially for low Reynold number e.g. for Reynold equal to 1 and 10. If the Reynold number higher than 10 pressure distribution for both cases is resemble. In generally ıt seen that from Fig.4 at stagnation point pressure has its maximum value and ıt has its minimum value at rear side wall of the cylinder.

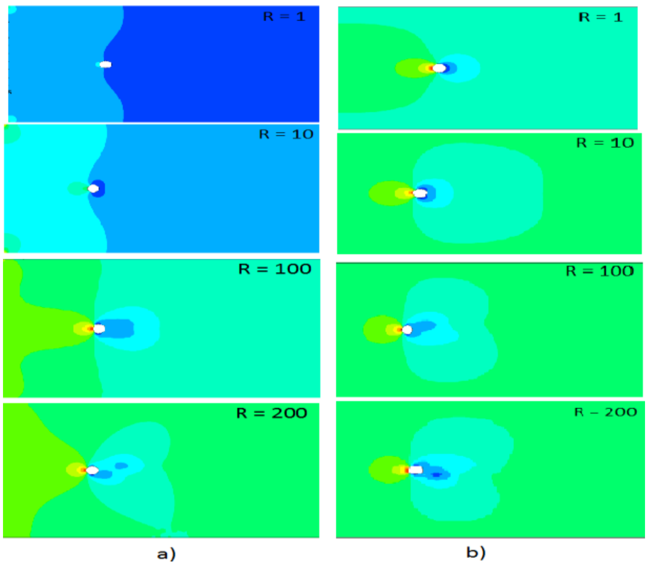


Figure 4: Static pressure distribution of water flow a) Case 1, b) Case 2

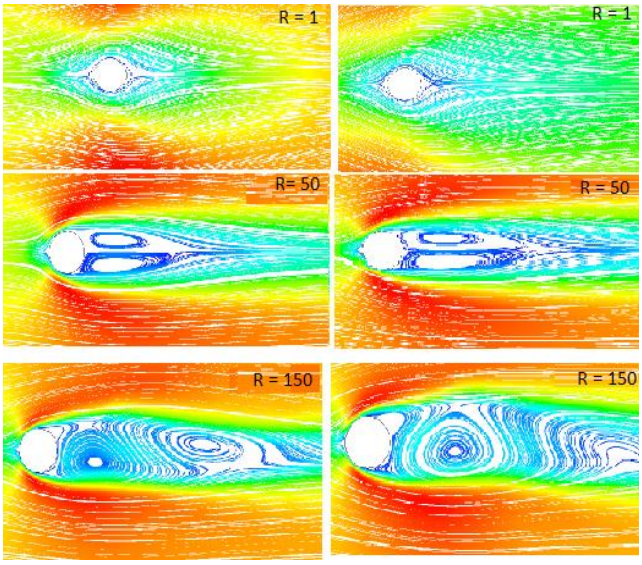


Figure 5: Velocity streamlines distribution of water flow a) Case 1, b) Case 2

Understanding pressure, velocity distribution, drag coefficient better we firstly need to understand structure of separation, wake region, boundary layer, vortex shedding also. In this sense velocity streamline distribution is shown with Fig.5 which prepared for water flow only. Because of similar configuration were observed for air and water, It is not necessary to show air velocity streamlines figure. According to both figures for low Reynold number, there are no vortexes at rear of the cylinder. So related flow almost can be described as potential flow. As ıt is known at low Reynold number the flow is defines as potential flow so there is no vortex and slightly separation yet.

Reynold value ranged from 10 to 50 the separation and eddies become clear. If Reynold number slightly greater, vorticities break off. For Reynold number equal to 150 Von-Karman vortex shedding come into existence. In this sense in [1] ıt was mentioned that there is no separation for $R < 5$, but for Reynold number from 5 to 40 there is a pair of vortices at wake region and also ıt was mentioned, according to reference study for Reynold number under 189 vortex shedding is laminar and two dimensional which almost compatible with our work.

Fig. 6 is shown vorticity distribution for case 2 for air flow. Vorticity distribution of case 2 also similar to case 1. According to [6] for Reynold number greater than 40 the boundary layer over the cylinder will separate due to adverse pressure gradient. Separation point where the shear stresses has its zero value. As seen from figure separation point change with different Reynold number. As a result of that, shear layer occur. Then the boundary layer contained amount of vorticities form around of the cylinder, then they cause shear layer to roll up in to a vortex [1, Sec. 2.2]. First vortex pair at present study was observed at Reynold number equal to 50 (Fig.5). It is significant saying that higher Reynold number the increases length of the shear layer and also vorticity length.

As we know drag coefficient more important parameter for blunt bodies which contact with fluid. It is undesirable condition for most flow dynamic especially for airfoils, submarines, risers etc. In this sense In Fig.7 drag coefficient versus with Reynold number is shown for case 1 and case 2. As seen from figures that as Reynold number increases the drag coefficient decreases for both cases and both fluids. This situation also has been confirmed in [7]. Another significant point may be that at Reynold number equal to 1, case 1 drag coefficient is higher than case 2 for the same conditions. It should be emphasized that for low Reynold numbers drag coefficient sharply decreases, on the other hand for higher Reynold number ıt decreases slowly. Wall effect causes increase of drag coefficient as compared to case 2 for opening condition. That is to say as we understood from results drag coefficient is depend on Reynold number and for higher Reynold number the lower drag coefficient occur.

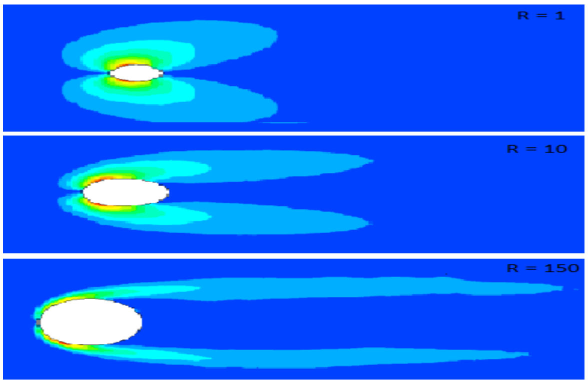
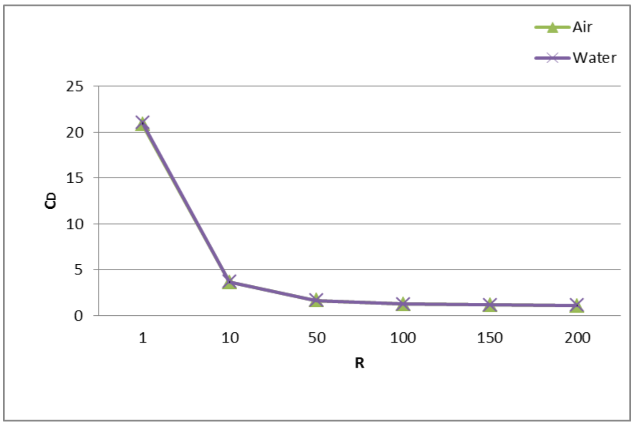
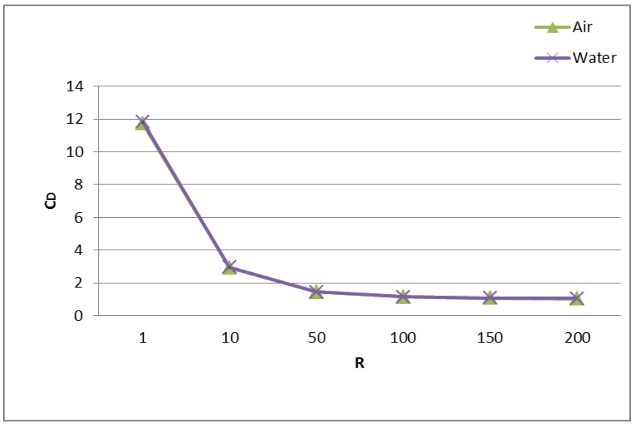


Figure 6: Boundary layer, shear layer, vortices

Drag coefficient also depend on boundary condition of domain in consideration, as you can see for wall vicinity to flow drag coefficient is increasing compared with flow without wall vicinity, on the other hand ıf there is no slip wall near the flow field drag coefficient is decreases of course. It is apparently understood that the drag coefficient of water and air flow is the same for the same Reynold numbers as seen from Fig.7 for both cases. Apart from these, drag coefficient closely related with shape of blunt body of course, but in present study this situation is not taken into account.





a) b)

Figure 7: Drag coefficient versus with Reynold number a) Case 1, b) Case 2

Conclusions

In this study as mentioned before for two different cases numerical analysis was done. Physical model of Case 1 and case 2 illustrated by Fig. 1, as seen from case 1 physical model solid cylinder placed at a channel, top and bottom of channel taken as no slip wall. It helps us to understand wall effect on flow around a cylinder. Then as seen from case 2 boundaries in question were handles as opening boundary condition which means that flow into domain possible. For boundary conditions in question, laminar steady state flow around blunt body was taken into consideration for different Reynold number and different fluids. From results accomplished velocity distribution, pressure distribution, streamlines colored by velocity were shown; comparison of drag coefficient in terms of different boundary conditions, different fluids and different Reynold numbers was taken under microscope. Results were important in term of velocity distribution effected by no slip wall in case 1, likewise drag coefficient results are significant of course. In the case of wall effect, drag coefficient is higher than the case of no wall effect for the same number of Reynolds. Also for the same Reynold numbers forming of the same values of drag coefficient for both fluids is interesting. In this sense further studies can be carried out by investigating the drag coefficient for different fluids at different Reynold numbers. Also investigation on different blunt bodies' shape, more important in terms of reducing drag coefficient. That is to say we believe that the work in question will be a good reference for future work in this field. It is possible to say briefly that:

1. Velocity distribution shows that for case 1 no slip wall boundary condition affected velocity distribution, especially make it zero at wall because of boundary layer, then of course effect all distribution from inlet to outlet. It is possible to observe the fully developed state of the velocity for a given Reynold number, i.e. the velocity distribution at a given Reynold number becomes similar to case 2. For Reynold number equal to 200 the velocity profile of both cases almost fully enhanced (Fig.3).
2. In generally at in front of the body because of the stagnation zone lowest velocity value observe, at rear of the cylinder because of the separation, vorticity effect caused velocity taking low value in this region. On the other hand velocity at top and bottom of cylinder take it maximum value (Fig.3).
3. At Reynold equal to 1 there is no any vortex. On the other hand First pair vortex occur for Reynold number equal to 50, then these vortex break off and wash down away from rear of cylinder. Von-Karman vortex shedding occurs at Reynold number around 150 (Fig.5).
4. Vortices figure show that for different Reynold number the region of separation point and length of the shear layer of course length of the vortices extended. As the number of Reynolds increases, the length of the vorticities increases (Fig. 6).
5. Drag coefficient result show that when the presence of the no slip wall condition (case 1), drag coefficient value increases compared with presence of the opening boundary condition (case 2). As increases Reynold number drag coefficient decreases. At low Reynold number this decline is so sharply. On the other hand reduction in the drag coefficient at higher Reynold number is slower (Fig. 7).

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Full Paper Proceeding ECBA-2016, Vol. 376- Issue. 36, 8-16

ISBN 978-969-683-009-3

ECBA -16

Exploiting Noisy Data Normalization for Stock Market Prediction

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Abstract

Stock market prediction has grown to be an interesting and intriguing research area in the field of big data analytics, predictive analytics and statistical analysis. The field of stock prediction has employed machine learning and artificial intelligence techniques to forecast the behavior of the financial market and to predict stock prices. Recently, social media has evolved to incorporate a massive amount and variety of textual data. The analysis of this information furthers the mining of public sentiment and opinions about real-time trends. In addition, the study of the inherently complex social media feeds promises new opportunities to discover empirical regularities, to measure economic activity and analyze economic behavior at high frequency and in real-time. However, the noisy and short nature of social media feeds mask this information: unlike structured news content, social media content is characterized by the presence of metadata related to social media sites (e.g. hashtags for Twitter), and the extensive usage of casual language, unstructured grammar, colloquial words, ad hoc multi-token nonstandard lexical items such as acronyms and abbreviations that need situational context to be interpreted and don't fit with traditional technical analysis simply based on forecasting models. Under those purposes and in order to meet the trading challenge in today's global market, technical analysis must be reconsidered. Before using any analysis model, data need to be preprocessed and regularities must be reviewed. So, the precision of the forecasting and prediction systems of the financial market and stock prices will be optimized and improved, also, the accuracy of the data analysis models will be higher than state-of-art models. In this context, this paper introduces the challenges of the noisy information overload from social media, gives a brief description of stock market prediction and its methodologies. Then, we discuss some of the current methods of stock prediction methodologies and emphasis the need of new improved ones which are more adapted to the context of noisy data. Finally, we present a new approach for the financial market forecasting and prediction which uses data preprocessing and normalization from noisy data in Twitter. The strong influence of the proposed data normalization model on the proposed approach's precision and accuracy can lead to a better results than traditional ones.

Keywords— Stock Market, Prediction, Natural Language Processing, Social Media, Data Mining, Normalization

Introduction

Stock market prediction or stock price forecasting is a major and important economic task in the planning of business activity. It has been an attractive and an appealing topic of research in several research fields such as engineering, mathematics, finance and computer science. Stock market prediction is a challenging task because of the noisy and intricate nature of the market. Its dependence to various factors such as unpredictable political events, product releases and the mood of the society based on its behavior and emotions [1]. Finally, due to the complexity of the market dynamics modeling present in different formats either structured numeric data or unstructured textual data which provide both quantitative and qualitative information about the stock price movement: quarterly and annual financial reports, news articles or internet. Therefore, as much as a large set of those factors and dynamics is exploited into stock market analysis, the more its prediction will be improved [2]. With the tremendous emergence of social media, information about neutral and public opinions or feelings is abundant and can be incorporated to clarify the public investment behavior. Furthermore, exploiting the social mood provided by social media can improve the accuracy of the stock market prediction because it might be one of the important influencing factors on its stock price [3].

In the recent times, social media has received a great deal of attention from researchers which looked at their exploitation in the daily stock price movement prediction's process. Social media sites especially microblogging ones allow people to share their personal thoughts or express their feelings and opinions about real-daily world events [4]. Twitter for instance, is the best corpus of valuable, freely available and rapidly updated data which provide researchers with early warnings about daily rise and fall in stock prices, and concise peeks into the public future

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purchasing behavior of consumers. Having all into consideration, exploiting social media textual data in addition to numeric stock data is very useful to increase the stock market prediction's accuracy and quality.

One major research task for tracking public opinions and sentiments about particular real-time trends from social media is Sentiment Analysis. On account of its evolving importance, sentiment analysis application in finance has attracted many researchers of computational linguistics [5]. The valuable Twitter data when equipped with text mining and sentiment analysis will offer a great intelligence of future public expectations and speculations about stock prices movements. Over the past few years, many research studies have approached the incorporation of Twitter with sentiment analysis or data mining techniques such as Ruiz et al. [6] used graphs which constrain time series to correlate the Twitter data activity with the stock price ups and downs. Eiji et al. [7] exploited Twitter data to catch the flu outbreaks. All these works emphasized the utility of Twitter as a massive source of fresh and valuable data that need to be interpreted in order to predict stock market and to forecast stock price movements.

Although the studies above have gained great performance, their prediction model accuracy is hampered by the noisy and short nature of data extracted from Twitter: Unlike structured, clean and formal news content, social media users often prefer communicating unconventionally with poor spelling, and unstructured grammar such as misspelled words (e.g. *thnk* is a variant of thank), abbreviations (e.g. *tmh* is an abbreviation of too much hate), slang (e.g. *nuh* is a common slang for no), or phonetic attributes of words (e.g. *l8tr* for later) that need situational context to be interpreted before being exploited in the stock market analysis. One possible solution to this problem is normalization, in which the informal text is converted into a more standard canonical form which until now, cannot be done by traditional stock market prediction approaches [8].

Under those purposes, the primary aim of this research paper is to investigate the influence of noisy data preprocessing and normalization on the optimization of stock market prediction models accuracy. It can be significantly improved by the exploitation of noisy data preprocessing enhanced by sentiment analysis from the social media. Our main contribution is that we propose a new approach for the financial stock market forecasting and prediction which uses data normalization and sentiment analysis from noisy data in Twitter. This proposed model exploit the strong influence of data normalization on the stock market prediction accuracy so as it can lead to a better results than traditional stock price movements prediction existing approaches.

The remainder of this paper is organized as follows: Section II gives a brief description of stock market prediction and its previous methodologies, discuss the present limitations and emphasis the need of new improved ones which are more adapted to the context of noisy data. The proposed model and hypothesis are emphasized in section III. Section IV compares the proposed model with other existing models. Finally, we discuss the comparison results and conclude this paper in section V.

Litterature Review

Stock market prediction is a very challenging topic of research. Many scientific researchers have addressed the capability of predicting the stock prices ups and downs. Below, we divide the state-of-art methods into two categories: Works that tried to solve the problem by incorporating fundamental and technical factors of the stock market and traditional tools. Second, works that exploit social media as a new tool and which use sentiment analysis techniques for tracking public mood in order to predict the stock prices rise and fall.

Traditional stock market prediction works

In general, the stock market prediction models usually incorporates two types of indicators: technical or fundamental ones. Simple or exponential moving average extracted from structured data are the best historical data researchers exploited as a quantitative measure for the stock price movement forecasting. On the other hand, macroeconomic dynamics extracted from unstructured data are the best fundamental indicators researchers incorporate as a non-historical quantitative measure for stock market prediction. Here after, we will discuss some works that performed stock market prediction with traditional approaches.

Wanjawa et al. [9] have used artificial neural networks for stock market prediction. It uses an artificial intelligent agent that learns the knowledge from the past events. The intelligent agent learns these past facts without any human supervision. Such artificial intelligence based approaches proved that stock prices forecasting can give performant results. Also, Schumaker et al. [10] have predicted the stock prices by exploiting financial news articles and stock price quotes. The proper nouns were extracted from news articles and combined with stock quotes in order to build a machine-learning algorithm with support vector regression. They proved that financial text mining can give great results but still one limitation found is that they only took into consideration the articles that were published during the time when the stock market was open: this is not realistic because other key information can be extracted before or after the opening of the stock market and can have a strong impact on the stock analysis. In addition, Ayodele et al. [11] have used fundamental and technical indicators to predict the stock prices by a hybrid model which combines fundamental and technical analysis. The technical indicators included opening and closing price, high and low price per day and were combined with fundamental indicators which included sell and buy rumors of the company. The joint approach results outperform the technical analysis results. Otherwise, the best known work for stock market prediction is the one conducted by Bollen et al. [12] which proved a very strong correlation between the public mood and the stock price movements when compared with fundamental and technical indicators impact on the stock. The public mood and emotions are present in unstructured sources such as microblogging sites. Therefore, it is essential to extract the information from unstructured sources and perform the analysis to make use of them in the prediction work. Hence, we present works that are based on opinions mining from unstructured data in order to exploit them in the stock price movement analysis.

Social media based works for stock market prediction

In recent years, many works have been oriented towards a new concept: social media. Many techniques have been applied to sentiment analysis for knowledge discovery in different domains including stock market prediction. With the emergence of social media the majority of works are based on Twitter as a major source for data-driven investigation to predict stock prices daily ups and downs. Below, we will discuss some social media based works for stock market prediction.

Bing et al. [13] studied the tweets and concluded the predictability of stock prices based on the type of industry. And, Brian et al. [14] proved the correlation of sentiments of public with stock rises and falls using Pearson correlation coefficient for stocks. Furthermore, Mao et al. [12] used a random baseline of public sentiment to decide every tweet as “bullish” and “bearish” the stock market. They showed a significant performance in the prediction process. But, Bar-Haim et al. [15] who exploited Twitter to identify expert investors to predict stock price ups by using a support vector machine to classify each stock related message to two polarities - “bullish” and “bearish”, proved that unsupervised approaches for identifying experts outperform random baseline approaches in precision. However, they didn’t offer a high performance in term of prediction. In addition, Ding et al. [16] have incorporated time series data as well as sentiments obtained from Twitter data in order to forecast stock price movements by extracting data from Yahoo! Finance. They trained their model with support vector machine which outperforms other training models in term of stock prediction’s accuracy. The Twitter data and time series data joint yielded to a performant prediction. The sentiment analysis method they used was based on just the keywords without the analysis of the situational context of the entire tweet. They also proposed that a more sophisticated tool could outperform sentiment analysis with better accuracy. Finally, Jianfeng et al. [17] have used data from Twitter to propose a new approach of semantic stock network (SSN) where the network nodes are the companies and the edges are the correlation between them. The proposed stock network shows a significant improvement on sentiment analysis based stock market prediction.

For stock market prediction, recently a lot of Twitter data is gathered in order to be mined to get relevant information relating to the prediction of stock prices and their daily rises and falls. There have been a plethora of research works that try to propose performing tools to improve the mining of social media data and its analysis in order to get accurate results. Those tools when applied to Twitter doesn’t perform with a simple list of positive and negative words but also with respect to superfluous, noisy words as well which provides an extra processing for social media analytics in the field of stock market prediction. Besides the fact that there is a lot of improvement in terms of the accuracy of stock prediction. This research field still needs a more accurate results: The presence of noisy words hamper the accuracy of analysis results. Social media text or noisy corpus is characterized by the presence of metadata related to social media sites (e.g. hashtags for Twitter), and the extensive usage of casual language, unstructured grammar, colloquial words, ad hoc multi-token non-standard lexical items such as acronyms and abbreviations that need situational context to be interpreted [18], which until now, cannot be done by existing approaches. Although the majority of social media based approaches incorporate data normalization in their prediction model, they don’t pay a great deal of attention to the context and the area of interest of noisy words by making a strong assumption that taking the first canonical form present in the correction dictionaries is the best one or they focus on spelling errors and orthographic noise. Which is not realistic owing to the fact that one noisy word can be restored to different standard forms on account of the context, the type of interest and the time period of the microblogging text and also because, social media noisy data that affect predictive studies and analysis go beyond simple orthographic errors or misspelling ones. Hence, a well-studied and accurate data normalization model will have a strong impact on any stock prediction model which will be used after as seen in *Fig. 1*. In the light of the above, this research paper aims at making it easier to predict stock by combining it with our context aware and type of interest, time period sensitive data normalization model [19][20]. Also, to construct an additional feature set from normalization of noisy data as well as technical, fundamental and sentiment analysis features in order to get a more accurate learning model. The proposed model is expected to lead to a better results than traditional stock price movements’ prediction existing approaches.

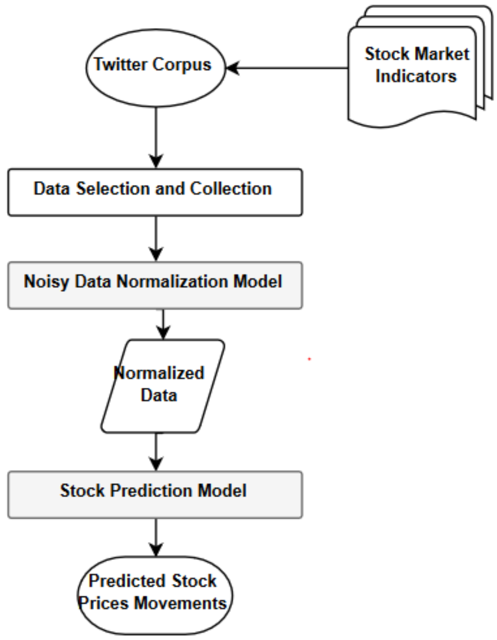

Figure 1: Impact of Data Normalization model on Stock Prediction model

Methodology

Only when normalization systems present accurate and high quality sources of data, prediction ones which exploit them will be able to give deep analysis and precise predictive studies. Thereby, we propose a novel approach for stock market prediction which exploit noisy data normalization and sentiment analysis. This approach is expected to lead to more accurate results and to be a more effective solution to the stock market prediction problem from noisy data. Below, we define the problem, then, we detail the proposed approach and its key steps.

Task Definition

Our model tracks public emotions about companies and their offered products and services, then predicts their stock price daily rises and falls from a noisy real-time stream of tweets after normalizing it. TABLE I shows the comparative study that emphasizes the difference and added value of our proposed model for stock market prediction from noisy data when compared to other models.

Table 1:
Comparative Study of Stock Market Prediction Models and The Proposed Model

Stock Market Prediction Models	Key Processes Of Stock Market Prediction		
	DATA COLLECTION	DATA PREPROCESSING	STOCK ANALYSIS AND PREDICTION
Technical Analysis Oriented Models	Time Series data		Technical analysis that includes support vector machines, artificial neural networks and logistic regression
Data Analysis Oriented Models	News articles Social media	Orthographic and misspelling errors correction	Mining the data obtained from textual sources such as social media sites like Twitter and financial news articles and analyze it
Hybrid Models	Time series data News articles Social media	Orthographic and misspelling errors correction Shortening elongating forms Removal of stop words and stemming	Considering technical, fundamental and sentiments analysis features

Proposed Model	Time series data News articles Social media Noisy Data	Orthographic and misspelling errors correction -Shortening elongating forms -Removal of stop words and stemming - Spam detection – Situational context interpretation and resolving slang and ad hoc abbreviations–Named Entities Recognition – Areas of interest inference	Considering technical, fundamental and sentiments analysis features Additional feature set constructed from situational context and inferred areas of interest of noisy data

The resulting pipeline of our proposed model is presented in *Fig. 2*. Given a raw stream of noisy tweets extracted with respect to a company's related keywords or stock indicators, it firstly filters out spam messages, secondly it tokenizes the stream, preprocess it, and normalizes it by interpreting meanings with respect to situational context found by weakly learning from ABB, a freely non-standard dictionary [19]. Then, we construct three levels of features: Financial features, Sentiment features and normalization features. Here after, all features are integrated together in order to generate weights for each one. Finally, we predict stock prices based on the generated weights. The strength of our model relies on the fact that it exploits a weakly supervised data normalization model based on situational context interpretation to reduce any noise and to extract additional features of sentiment analysis and predictive studies. This new model is expected to give a high accurate results than other state-of-art models because it uses an additional feature based on noisy data normalization. Therefore, it promises an accurate analysis of facts and an outperforming predictive studies of the stock market.

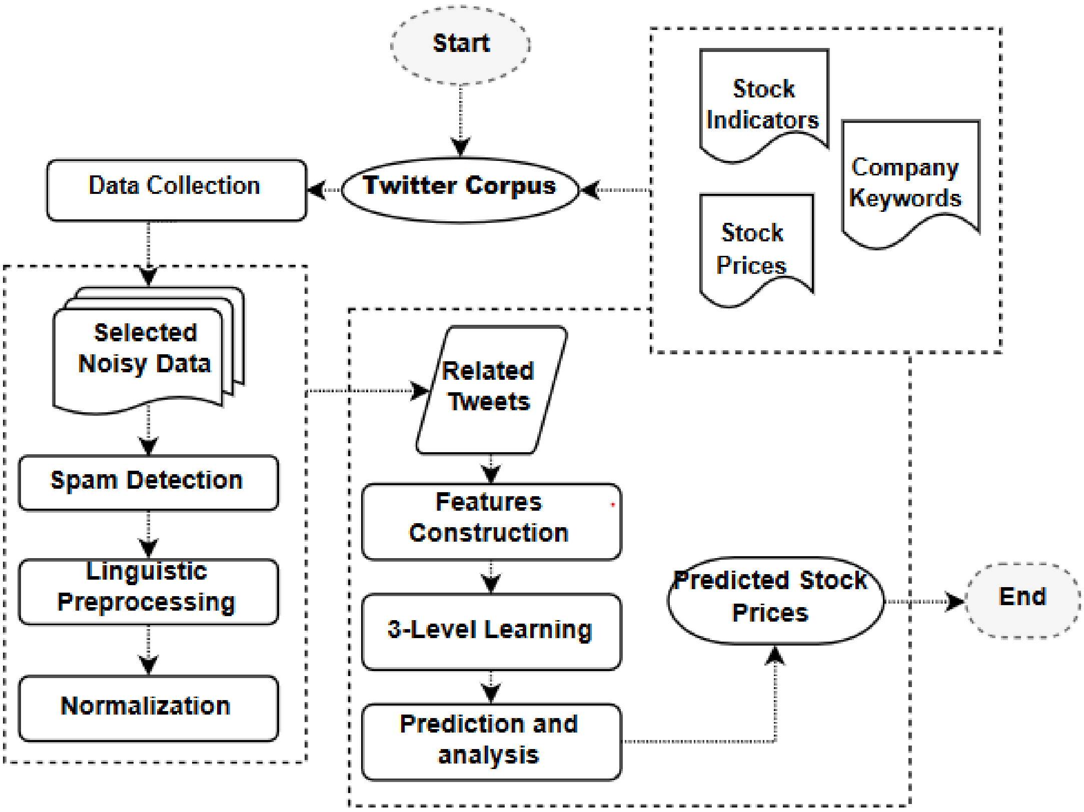

Figure 2: The proposed Stock Market Prediction Model

The Proposed Approach

Data Collection

Unlike the traditional data sources such as blogs and forums, social media emerged as a way of communication over the last decade to be the best rapid and real time source of information. Hence, the data is gathered from the best microblogging site Twitter which contains a real-time data stream of short messages or tweets. The tweets are collected using Twitter API and filtered using keywords related to companies and the stock market indicators. We are interested in tracking not only the opinion of people about the company's stock but also their opinions about products and services offered by this company. The analysis of people's opinions about a company's products and services has a strong influence on its stock price movements forecasting. The collected data must be preprocessed and cleaned in order to get only relevant information.

Noisy data Normalization Model

As a raw data, tweets are highly susceptible to noise. In other words, tweets consists of many acronyms, emoticons and mega elements that need situational context to be interpreted or even unnecessary data like pictures and URL's. The quality of raw data affects the sentiment mining results. In order to help improve the quality of the data and consequently, of the mining results raw data is preprocessed in order to improve the efficiency and ease of the mining process. So tweets are preprocessed and normalized to represent correct emotions of public depending on the context. For preprocessing of tweets we employed three major processes. Below, we describe each process:

Spam Detection

Spam consist of messages which don't provide any relevant information or useless ones. Following Katsios [21], we exclude all tweets that link to untrusted web sites. Then, we compute the spam score to filter out higher scored spam messages than a learned threshold by:

$$S^* = \frac{|u|+|h|+|l|+|s|+|n|}{|t|}$$

Where: $|u|$ is the number of user mentions, $|h|$ is the number of hashtags, $|l|$ is the number of web links, $|s|$ is the number of spam words (detected from a predefined list), $|n|$ is the number of non-words character, and $|t|$ is the total number of tokens.

Preprocessing of the Datastream

After filtering out spam tweets, we apply our linguistic preprocessing component [19] to eliminate all Twitter's mega elements with a regex pattern tokenizer that breaks the text into tokens and reject all mega elements (hash-tags, user IDs…), then we shorten any alphabet that is repeated more than three times to two letters (shoooow is shortened to show). Finally, we eliminate all the spelling errors and unintentional ones by one to one mapping with canonical forms from the English standard dictionary.

Normalization

All tweets outputted by the linguistic preprocessing component, are additionally passed through our casual English normalizer [19] in order to resolve multi-token non- standard items as seen in the flowchart in *Fig. 4*. We first, detect a tweet's noisy zone which is composed by multi-token non-standard items existing in that tweet as:

$$NZ(T_i) = \left\{ \bigcup_{j=1}^{p} w_j \,/\, w_j \in ABB \right\}$$

Where: w_j is j^{th} multi-token non-standard item in the tweet T_i, and ABB is a freely online non-standard dictionary.

Then, we infer an adequate area of interest for elements in the noisy zone by constraining each detected element over areas of interest based on its set of possible areas of interest in ABB dictionary. Here after, based on the inferred area of interest, we extract each tweet's correct zone: a set of all canonical forms having the same area of interest inferred as:

$$CZ\left(T_i\right) = \left\{ \bigcup_{j=1}^{q} c_j \,/\, A_{c_j} = A_{w_j,i} \right\}$$

Where: c_j is canonical form of j^{th} multi-token non-standard item, A_{c_j} is its area of interest, and $A_{w_j,i}$ is the inferred area of interest of w_j.

Finally, we normalize each element of the noisy zone by its popular correct element from the correct zone by computing the popularity score of the corresponding ranking matrix as:

$$P_{c_j}^{\ *} = \max_{n\in\{1,q\}}(\sum_{m=1}^{s} r_{nm}) \,/\, R = \left(r_{n,m}\right) \in \mathbb{R}^{q\times s}$$

Where: s is the number of search engines, r_{nm} is the number of times c_j is searched in a known time period, and R is the corresponding matrix of ranking.

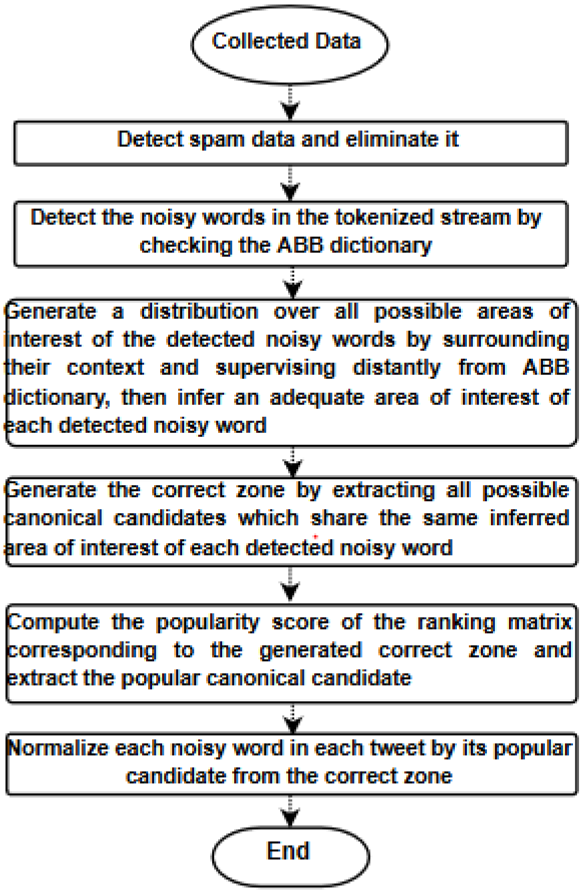

Figure 3: Data Normalization Model Flowchart

Stock Market Prediction Model

After normalizing noisy data and eliminating all non-relevant information, preprocessed data pass through our prediction model by three processes: Technical, fundamental features, sentimental features and normalization features construction, a three-Level learning model that generates the optimal combination of the three sets of features, and finally, the prediction of stock prices.

Features Construction

The adopted features are indicators from technical, fundamental and sentiment analysis as the majority of previous works, the difference is that we combine them with an additional feature constructed from areas of interest and recognized named entities inferred by the normalization model to get more accurate results. The technical and fundamental features are constructed from historic data and sentiment features are constructed from social media as seen in [22] [19][20].

3-Level Learning

The three features sets constructed must give a key information to be learned. Here after, the features are fed to the three-Level Learner in order to be estimated. Following Devi et al. [22], we use a Multiple Kernel Learning Support Vector Machine (MKL-SVM) because it supports features from multiple sources rather than traditional Support Vector Machine (SVM) and its ability to select the optimal kernel and parameters from a larger set of kernels. Hence, the features constructed from technical and fundamental stock indicators extracted from financial documents, the features constructed from sentiment analysis from public tweets, and the features constructed from areas of interest of noisy data inferred by the normalization model constitute kernels. The three-Level Learning component learns an optimal combination of the predefined kernels by:

$$K_{3-L}(a,b) = \sum_{i=1}^{n} \beta_i K_i(a,b) \; / \beta_i \geq 0, \sum_{i=1}^{n} \beta_i = 1$$

Where: β_i is the vector of weights of each kernel composed by the three constructed features sets, and K_{3-L} estimates the weights for each of the three feature sets to find the optimum combined kernels.

Prediction and Analysis

After getting the optimized combination of kernels by the three-Level Learner, we predict the adequate prices of the next trading day, and evaluate the three features sets by comparing actual prices and predicted ones.

Results

Our model track public emotions about companies and their offered products and services, then predict their stock price daily rises and falls from a noisy real-time stream of tweets after normalizing it. Fig. 4 shows the stock market prediction pipeline for three companies Maersk Group, Dell Inc. and Coca-Cola. Where at (1), we collect the suitable data by extracting tweets from Twitter with respect to keywords related to the three companies and stock indicators from financial documents or news articles. Then, we eliminate spam data (2). Here after, we preprocess and normalize extracted data (3). Finally, we construct adequate features (4) and generates predicted stock prices for each company (5). We have to note that we are still in the earlier implementation stages of our model.

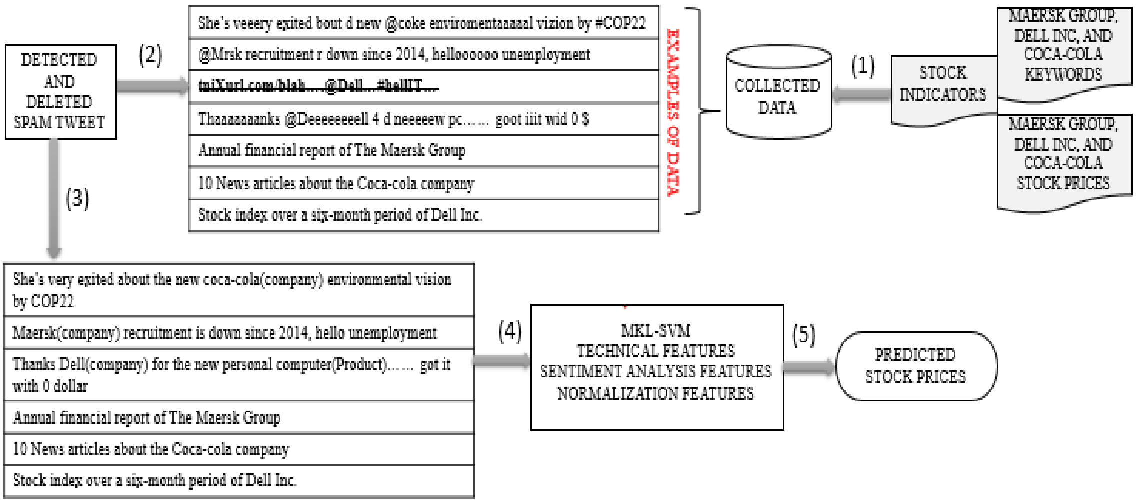

Figure 4: Predicted stock prices process flow for MAESK Group, Dell Inc. and Coca-cola

Discussion & Conclusion

The stock market forecasting and prediction is a very challenging and highly complicated task because it is influenced by many factors: Technical, fundamental, sentimental and normalization factors. The stock prices indicators are generally dynamic and noisy. Although the majority of existing approaches incorporate data normalization as well as sentiment analysis in their prediction model, they don't pay a great deal of attention to the context and the area of interest of noisy words by making a strong assumption that taking the first canonical form present in the correction dictionaries is the best one or they focus on spelling errors and orthographic noise. Which is not realistic owing to the fact that one noisy word can be restored to different standard forms on account of the context, the type of interest and the time period of the microblogging text and also because, social media noisy data that affect predictive studies and sentiment analysis go beyond simple orthographic errors or misspelling ones. The sentiment analysis features as well as technical and fundamental features aren't enough to give an accurate predicted price movements. The accuracy of stock price directional movements can be significantly improved by the incorporation of an additional feature set constructed from normalization from noisy data. Early stages of tests indicate that there is a strong impact of normalization features on stock market price change. Hence, a well-studied and accurate data normalization model will have a strong impact on any stock prediction model. Under those purposes, we proposed to combine the stock prediction model with our context aware and type of interest, time period sensitive data normalization model [19][20]. Second, to add a normalization feature constructed from areas of interest inferred for noisy data to the MKL-SVM learner. The proposed model is expected to lead to a better results than traditional stock price movements' prediction existing approaches.

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Full Paper Proceeding ECBA-2016, Vol. 376- Issue. 36, 17-23

ISBN 978-969-683-009-3

ECBA -16

Intracellular Ag Nanoparticle Synthesis using Water Lettuce (*Pistia Stratiotes*)

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Abstract

Nowadays plant extracts have been extensively used for biosynthesis of nanoparticles. However, *in vivo* synthesis of engineered nanomaterials, which can be major process for mass production, is little documented. It is known that aquatic plants can absorb and accumulate large amount of metal in their tissues. This paper reports intracellular synthesis of AgNPs using a freshwater aquatic plant (*Pistia stratiotes*). In this study, *P. stratiotes* samples exposed to $AgNO_3$ (10 mg/L) for 2 days. After the exposure period, nanoparticles were obtained using freeze-drying and freeze-thawing method. Characterization of obtained nanoparticles was conducted by UV–Vis spectroscopy, scanning electron microscopy, X–ray diffraction, Fourier transform infrared spectroscopy and dynamic light scattering. According to UV–Vis absorption spectrum maximum absorbance peak was observed at 447 nm which is the characteristic peak of Ag nanoparticles. The SEM image showed that the AgNPs formed with a spherical shape. It was determined that presence of biochemical agents such as carbohydrates, glycosides and flavonoids in *P. stratiotes* cells play important role in AgNP formation. Zeta potential analysis of AgNPs showed the zeta value at – 20.4 mV, which suggests the higher stability of synthesized AgNPs. XRD results confirmed the formation of AgNPs. Obtained AgNPs showed bactericidal activity against pathogenic bacteria *E. coli*. The present study illustrated an innovative way for producing large amount of antimicrobial AgNPs which can be used for different applications.

Keywords— Intracellular Synthesis, Silver Nanoparticles, *Pistia Stratiotes*, Characterization, SEM

Introduction

Recently, green synthesis methods have been developed and used as alternative methods in nanoparticle (NP) synthesis in order to overcome limitations of conventional methods. One of the green methods in NP synthesis is using plant extracts. In addition to, it has been showed that NP's can produce intracellularly as well [1, 2]. Plants have multiple defense mechanisms to protect themselves against toxic effects of xenobiotic coming from environment. Uptake of excessive levels of heavy metals into the cytoplasm may be prevented by binding to the cell walls; detoxification also occurs at the molecular level [3, 4 and 5]. Thiol-containing compounds such as metallothioneins, glutathione and phytochelatins play most important role in this mechanism. Complexation with these organic molecules reduces the cytotoxicity of metal ions and allows metal transport and storage in vacuoles. Nanomaterials may be produced as spheres, triangles, hexagons, rods, wires and tubes, which suit specific applications [6,7]. To compensate the growing demand for nanomaterials, developing an eco-friendly synthesis approach is inevitable. Several applications of nanoparticles including in fields such as electronics, health, catalysis, water purification are known. Silver nanoparticles (AgNPs) have prominent roles in areas of medicine, nanosensors, food chemistry, agriculture, food packing, cosmetics and textiles.

Literature Review

It is well established now that many organisms can produce inorganic materials either on intra- or extra-cellular level. Recently, yeast (*Schizosaccharomyces pombe*) mediated synthesis of CdS nanoparticles has been reported by Al-Shalabi and Doran [8]. Researchers obtained intracellular CdS quantum dots using hairy roots of tomato (*Solanum lycopersicum*) as well. In another study conducted by Ouyang and Sun silver sulfate quantum dots (Ag_2S QDs) were synthetized in wheat endosperm cells [9]. Producing of Ag nanoparticle intracellularly using actinobacteria was shown by Otari et al. [10].

Pistia stratiotes (water lettuce) is a freshwater invasive weed that is found easily throughout the tropics and subtropics. Its ecology has been studied extensively. It can be used in phytoremediation of xenobiotics such as heavy metals. In a study conducted by Odjegba and Fasili, it was determined that high amount heavy metals (such as Ag,

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Cd, Cr, Cu, Hg, Ni, Pb and Zn) can accumulate in shoot and root of *P. stratiotes* [11]. In our survey, we could not reach any study related to characterization of accumulated Ag (size, shape etc.) by aquatic plants. The aim of this work is to investigate the whether an aquatic plant (*P. stratiotes*) can be used for production of AgNPs. Finding of this study will be useful for studies that are related to Cu nanoparticle biosynthesis.

Methodology

Sample Cultivation

P. stratiotes seedlings were purchased from a local supplier. Prior to the experiment, containers were disinfected by immersion in 1% (v/v) NaClO for three to five minutes. Containers were then rinsed three times with distilled water [9]. Plant samples were washed in tap water and acclimatized for three days in a climate chamber with a water temperature of 15°C, a relative humidity of 70% and light/dark photoperiod of 16 h light/8 h dark. Containers were mildly aerated.

Experimental Design

The experiments conducted in the present study were set-up in triplicate. The Ag solutions utilized in the present study were prepared from $AgNO_3$. Only one individual plant sample was exposed to 10 mg/L of Ag maintained in 10% Hoagland's solution in separate 400 mL conical flasks. The plants that were not exposed to Ag served as the control groups of this experiment. Flasks were placed in a climate chamber under the aforementioned conditions for 4 days. Flasks were not aerated during experiment. The change that occurred in the volume of the solution within the flasks due to evapotranspiration was compensated for by the addition of double distillated water. At the end of the exposure experiment, the resultant plant samples were collected and sieved with a plastic griddle. Each plant was rinsed with deionized water, drained, and then blotted on paper towels for 2 min. Roots of Ag exposed plants were separated and used in purification studies.

Purification of Cu NPs (Freeze-drying and freeze-thawing)

Freeze-drying and freeze-thawing procedures were conducted according to Al-Shalabi and Doran [8]. Root samples were frozen at −70°C, and then freeze-dried overnight. The dried biomass was ground using a mortar and pestle, placed in a Falcon tube with extraction buffer and vortexed. The mixture was frozen overnight at −20◦C. After that, thawing procedures are achieved. Samples were then thawed in Falcon tubes at −20 °C, on ice for 2–3 h. Ice-cold extraction buffer was added with vortexing. Another volume of extraction buffer was added and the roots were frozen again at −20 °C overnight, followed by thawing. The samples were vortexed and then centrifuged at 11,000 × g for 20 min at 4 °C. The supernatants from all extraction cycles were pooled and filtered.

Instrumentation and Characterization

The absorption spectra of Ag NPs and *P. stratiotes* root extract solutions were recorded using UV-Vis spectrophotometer (PerkinElmer). A few drops of concentrated aqueous solution were deposited on the stub covered with aluminum foil and it was left to dry for overnight. Then the stub was coated with gold by a sputter device to obtain clear scanning electron microscopy images (SEM) (ZEISS EVO LS10). The same sample preparation was followed for generating scanning tunneling microscopy (STM) (ZEISS EVO LS10) images. Typically, a few drops of aqueous solution were deposited on a carbon-coated copper grid and left to dry for overnight to get clear STM images. Energy-dispersive X-ray spectroscopy (EDX) was used for elemental analysis of CuO NPs. The structure of Ag NPs was analyzed with X-ray diffraction technique (XRD) (BRUKER AXS D8). The presence of Ag NPs was verified with FT-IR Spectrometer. The effective size of Ag NPs and their surface charge were measured with dynamic light scattering (DLS) and Zeta Potential (Malvern), respectively.

Antimicrobial Activity

The agar diffusion method was used for the determination of antimicrobial activities of the AgNP's. Escherichia coli O157 were selected as test organism. At the end of the exposure, petri dish was examined for zones of growth inhibition, and the diameters of these zones were measured in millimeters.

Results and Discussion

At the end of exposure experiment, it was observed that colourless roots of *P. stratiotes* turned into the brownish black (Fig. 1). This was also determined as evidence for AgNP formation [12]. In a study conducted by Castro-Longoria et al. *Neurospora crassa* (a filamentous fungus) exposed to the aqueous solutions of 10^{-3} M of $AgNO_3$ and similarly colour changing was observed. UV–visible spectrum of the aqueous medium peaked at 447 nm corresponding to the absorbance of Ag/AgO nanoparticles (Fig 2). Near absorption peaks were observed by earlier studies for Ag NPs [13]. Besides, absorption peak was broad. Due to rich ingredient of plant, several molecules in plants may contribute to Ag NPs formation and caused a broad absorption spectrum. It is well known that the shape and size dependent surface plasmon resonance properties of metallic NPs determine their UV-visible absorption points. In general, increasing size of NPs results in a remarkable red shift (right shift) of wavelength absorption spectrum while a blue shift (left shift) appears with smaller size NPs. Because of the presence of metabolites in cells and on the surface of Ag may prevent to monitor a sharp absorption peak of AgNPs.

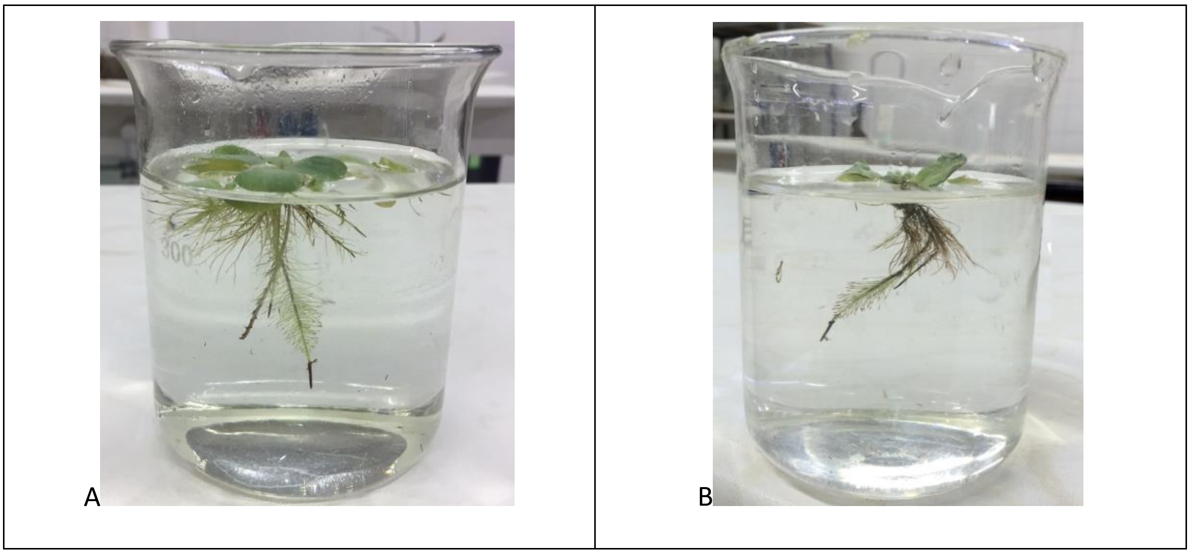

Figure 1: Images of *P. stratiotes* sample before (A) and after (B) exposure to 10 ml/L $AgNO_3$ for 48 h.

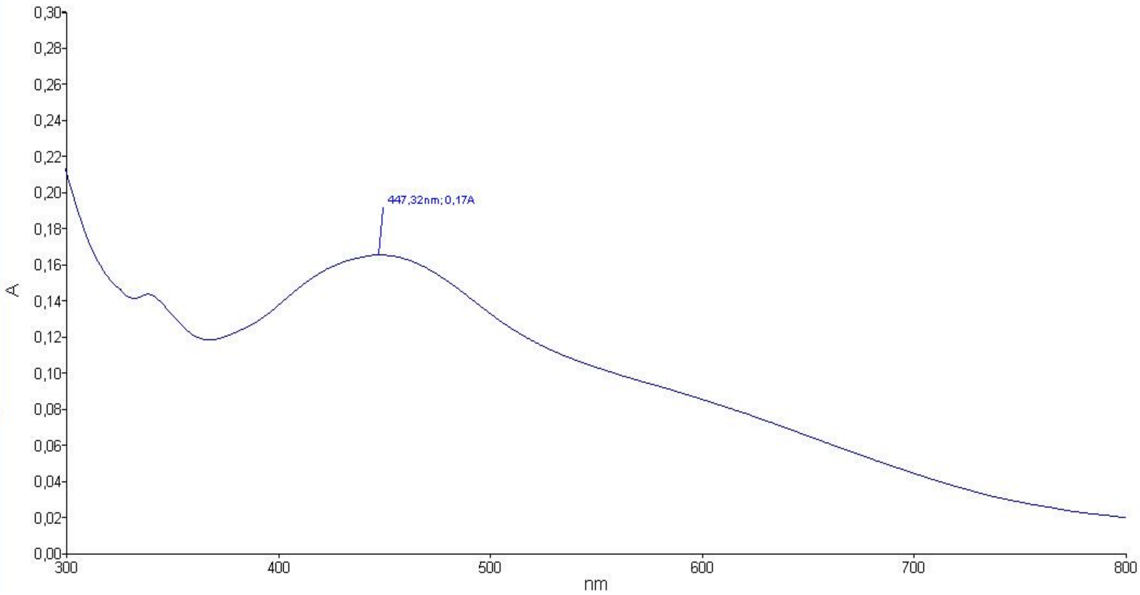

Figure 2: UV-Vis absorption spectra of *in vivo* synthetized AgNPs.

Results of FT-IR analysis have been shown in Fig. 3. The strong bond revealed at 3246.99 cm^{-1} (O–H stretching) can be assigned to alcohols and phenols. Peak occurring at 1073.51 cm^{-1} could be due to stretching of C-O bonds. The peak at 1636.12 cm^{-1} arises from C=C stretching modes. Observed peak at 589 cm^{-1} was determined as characteristic band vibration of Ag-O. It can be concluded that functional groups of metabolites which are found in plant cells can be involved in Ag nanoparticle synthesis.

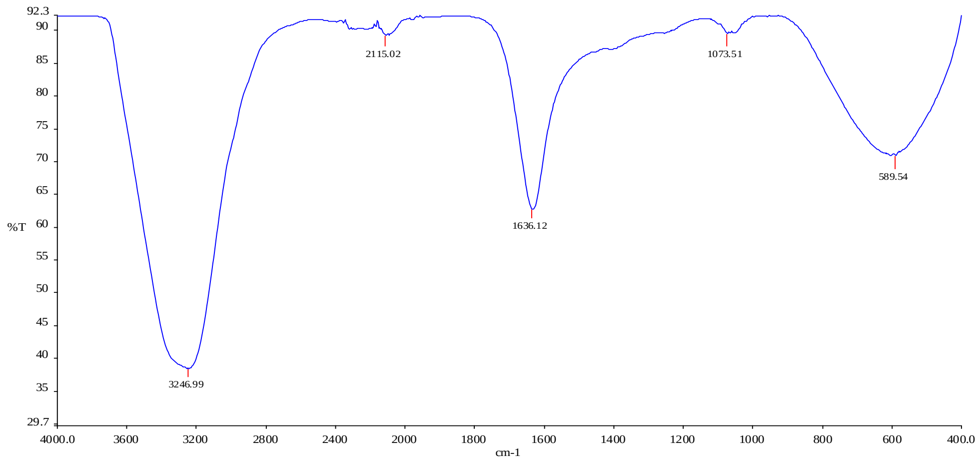

Figure 3: FT-IR spectrum of *in vivo* synthetized AgNPs.

Dynamic light scattering (DLS) results showed that effective diameter of Ag NP was between 200-400 nm (Fig. 4). The charge type and charge density on the surfaces of Ag NPs were recorded with Zeta potential measurements. Negative value of Zeta potential (−20.4 mV) confirms stability of intracellular AgNPs (Fig. 5). The SEM image of AgNPs showed that nanoparticles are spherical in shape and less than 70 nm. Generally, size of nanoparticles was found between 5 to 70 nm. It can be claimed that large size of AgNPs are formed owing to aggregation of nanoparticles. In a similar study conducted by Otari et al. it was found that size of spherical AgNPs obtained intracellularly in actinobacteria [10].

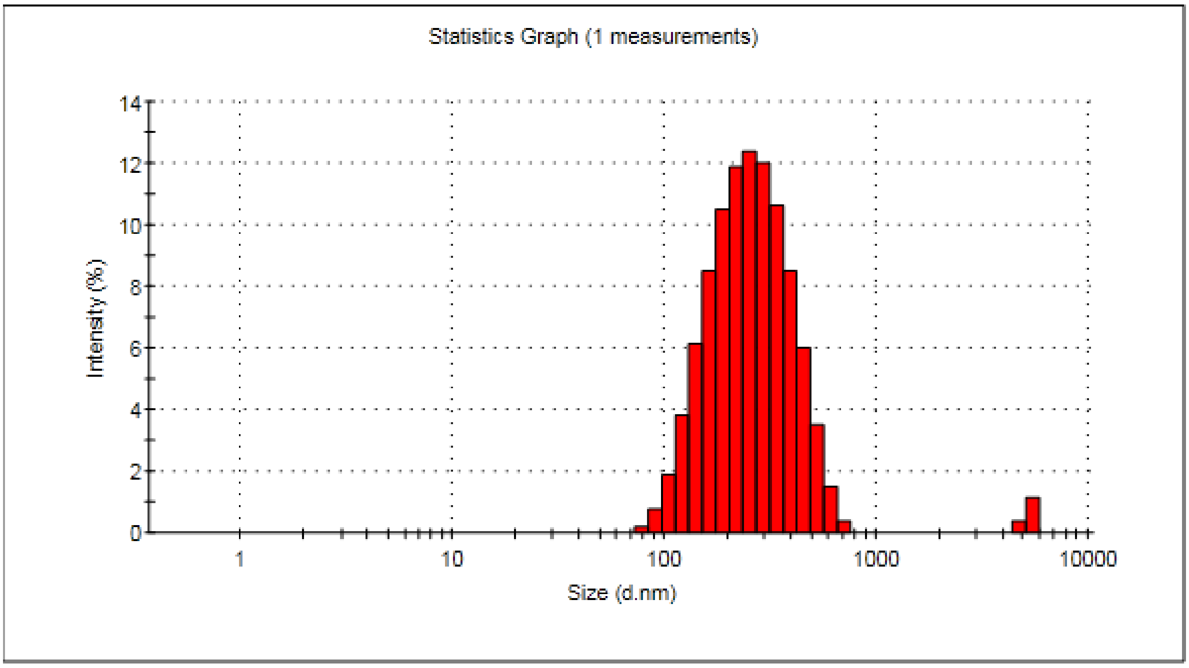

Figure 4: DLS analysis results of *in vivo* synthesized Ag NPs

			Mean (mV)	Area (%)	Width (mV)
Zeta Potential (mV):	-20,4	Peak 1:	-20,4	100,0	6,37
Zeta Deviation (mV):	6,37	Peak 2:	0,00	0,0	0,00
Conductivity (mS/cm):	0,219	Peak 3:	0,00	0,0	0,00
Result quality	Good				

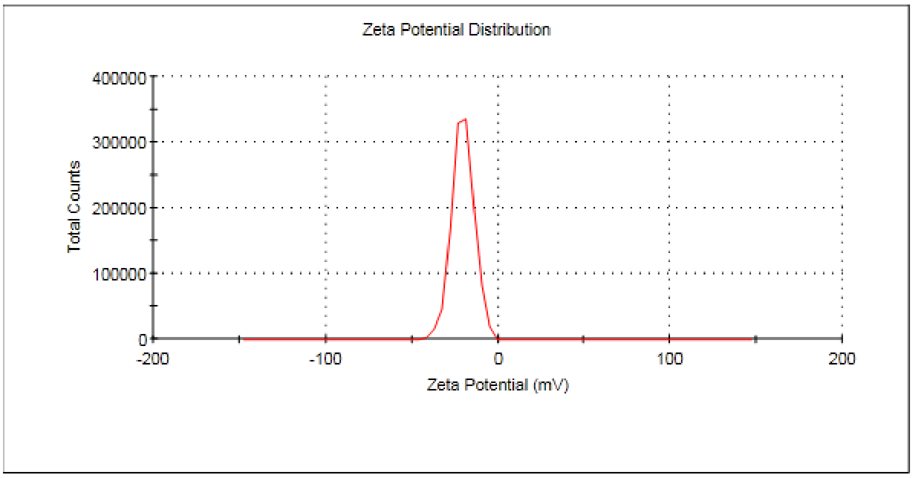

Figure 5: Zeta potential determination by dynamic light scattering (DLS)

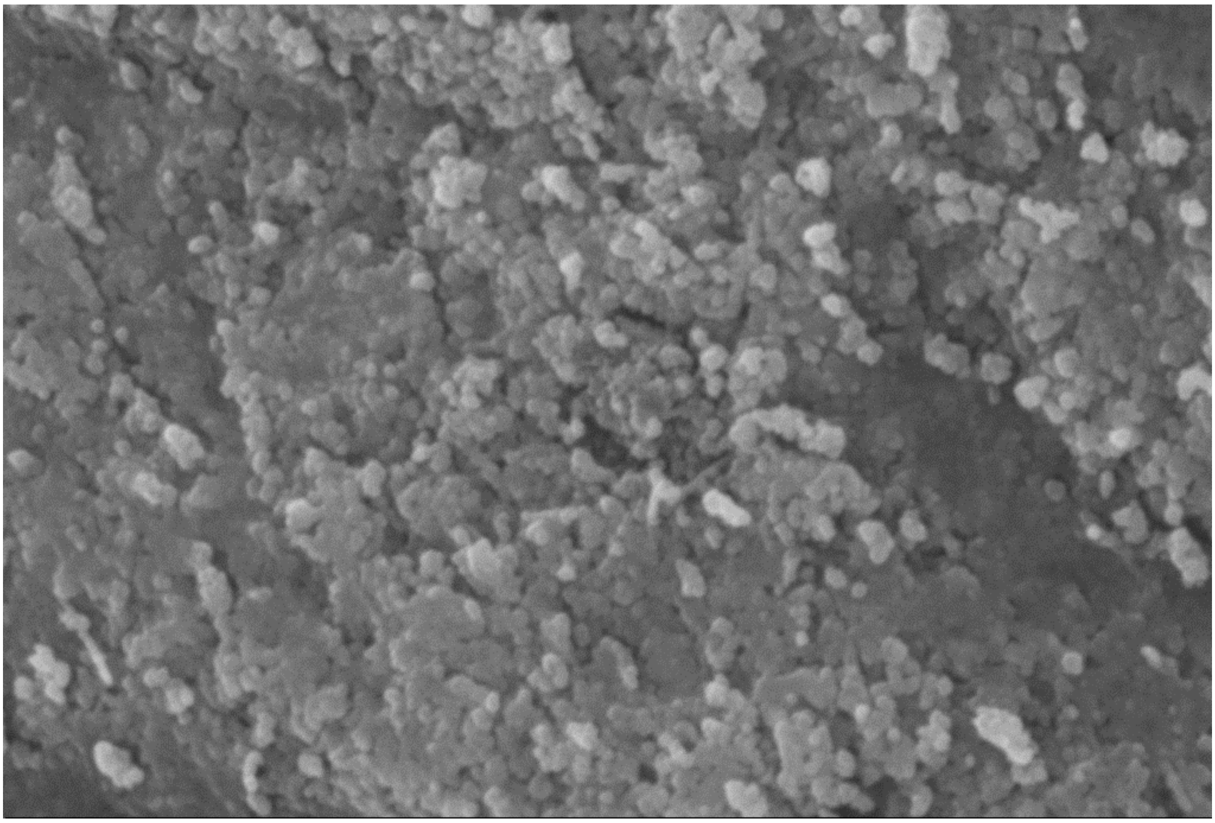

Figure 6: SEM image of *in vivo* synthetized AgNPs

Because of their antimicrobial properties silver products has been used for years in the medical field. Up to date, exact effect mechanism of AgNPs is not be clarified. However, there are plenty of studies stating high antimicrobial activity of biologically synthetized AgNPs. For example, Otari et al. obtained AgNPs showed bacteriostatic and bactericidal activity [10]. Our results are compatible with theirs.

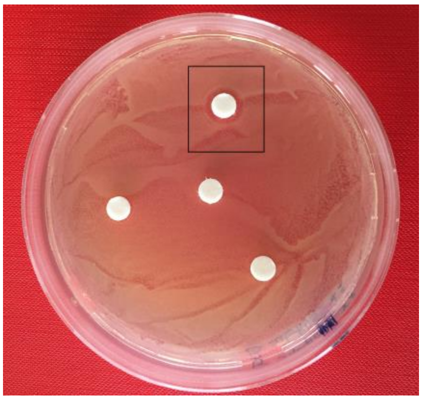

Figure 7: Photographic images of zone of inhibition of in vivo synthesized AgNPs against *E. coli.*

Conclusion

P. stratiotes treated with 10 mg/L $AgNO_3$ were used to produce Ag NPs. The biosynthesis of AgNPs in *P. stratiotes* may draw particular attention because it is simple, accessible, and environmentally benign. Combination of freeze-drying and freeze-thawing method was suitable for AgNPs recovery. The plant ingredients acted as both reducing and stabilizing agent to form AgNPs. In vivo nanoparticle synthesis can be evaluated as a simple, less time consuming, cheap and large scale production method. Besides, functional and biocompatible AgNPs can be obtained. Moreover, the production of CuNPs by in vivo is desired for industrial processes and requires further investigations. Further studies to produce intracellular nanoparticle would be attempted by using the aquatic plants.

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