Desalination and Water Treatment
www.deswater.com

doi:10.5004/dwt.2017.21298

87 (2017) 209–215
August

Modelling and sensitivity analysis of varying roughness effect on dispersion coefficient: a laboratory study

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Received 30 January 2017; Accepted 7 August 2017

ABSTRACT

Frequent disposal of effluent in rivers or streams in vicinity where the inhabitants rely majorly on it for domestic and agricultural purposes is dangerous, and that makes it relevant for precise modelling of dispersion coefficient or dispersion number. This will reduce under-estimation and over-estimation of this parameter as well as reduce frequent pollution assessment which have proven not to be sustainable. However, obtaining a model that will include all required parameter is still in process. This study considered the effect of varying roughness—which is the true nature of streams and rivers and its effects on the estimation of dispersion coefficient. It revealed that when varying roughness is increased by 1-unit, there will be an increase in dispersion number by 0.693 (t-statistics = 4.278; $p < 0.05$. In addition, an increase in 1-unit in the dispersion number value will require a decrease of both DO (t – ratio = –7.802; $p < 0.05$) and velocity (t – ratio = –4.992; $p < 0.05$) by 0.316 and 0.687 respectively. Sensitivity analysis further showed that roughness (K), dissolved oxygen (DO) are pertinent variables to be considered when dispersion co-efficient is to be modelled and have been previously left out. Furthermore, the ECM model generated, with $R^2 = 0.98$, *prob*(*F–statistics*) < 0.005 and Durbin-Watson t-statistics of 2.107 respectively shows statistical significance of the model. Hence, it is suggested that varying roughness or roughness and DO should be introduced in dispersion coefficient or dispersion number models to improve its accuracy.

Keywords: Dispersion number; Dissolved Oxygen; Error correction method (ECM); Pollution; Tracer studies

1. Introduction

Surface water—streams and rivers, are susceptible to constant pollution if not controlled as it is perceived by some people as a conduit for the transport of waste, and that it cleanses itself as dilution and dispersion takes place downstream. However, most people are ignorant on the possible harm these pollutants present in the river can cause to the users downstream as it is utilized for irrigation and domestic purpose among other uses [1]. This indicates that obtaining water of good quality for our basic and daily needs could be difficult thereby making water an at-risk commodity [2]. To circumvent this, there is a need for river or stream monitoring to help reduce local pollution. This will help to quickly identify if there are any significant changes in the current river ecosystem characteristics when threatened adversely, also to improve the general health status of the river and to come up with auspicious policies for proper river management—as in the case of the Water Framework Directive in 2000 [3]. For laboratory [4,5] or field study [3,6,7] purposes, trace studies (TS) using common salt as pollutants have been relatively and effectively used to mimic its transport in streams or rivers. Generally, it is understood that when tracers—irrespective of the type are released, the tracer is first diluted, thereafter, mixing occurring within the length and breadth of the channel or river and finally, the tracer transport process is completed by longitudinal dispersion [3,8,9]. The proper measurement of this parameter will provide a proper understanding—estimating and predicting, in the

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transport pattern of pollutants [10,11], intake and outfall structures designs [12], improve general water quality and pollution control related issues [1]. However, to achieved this, there is a need to engage in a tool that can accurately measure and predict the concentration and spread of pollutants [9]. This maybe involving, even as there exist quite a number of models for this purpose yet significant differences among the various results obtained [13–15]. Likewise, this disparity may be due to the inability of the models to capture all the model parameters in the existing equations found in the literature and among other reason yet unknown. But if the parameters in the model are carefully selected, it could reduce the time and cost of sampling [4,16,17], erase to a large extent, overestimation and underestimation of dispersion coefficient and minimise the rigorous process associated with practical experimental processes [18]. On the other hand, various factors have been reported in the literature to have influence on the dispersion coefficient, and which includes but not limited to pond walls characteristics, the value of Reynolds number, velocity of the flowing liquid [19] and aspect ratio [5,20]. In his study, it showed that the presence of roughness in channels could have effect on the dispersion coefficient value. This was expressed using a simple regression model. However, in the study, the values of R^2 reported showed the overall performance of the model and not the individual contribution of the model parameters. This may be important as some parameters may not be good contributors or statistically significant. In addition, the multiple regression used was not able to show the contribution of individual parameters present in the model. Also, the roughness expressed was not varied as that may not represent the real characteristics of a natural river or stream conditions which may affect the decisions of the model generated and limiting its applicability in that regard.

In the literature, the importance and type of sensitivity analysis used have been well reported [21–25] and it is necessary therefore, that performing it in a model generated is necessary. Therefore, the aim of this study is to model the effect of varying roughness on dispersion coefficient and perform a sensitivity analysis on the model parameters using Error Correction Method (ECM) as a statistical approach. Experimental data are likely to vary because of equipment and environmental conditions among others. The use of ECM technique will help take care of such variability. In addition, time series data and variables need to be tested for both cointegration and stationarity with the unit root test and cointegration test for short-run and long-run stability of the coefficients of the variables [26]. The stationarity of the variables is achieved by using augmented dickey fuller (ADF) while cointegration is achieved using the CUSUM and CUSUM squared test.

2. Data analysis

The arrangement of the dataset used for sensitivity and modelling was achieved using Microsoft excel 2013. Also, eViews version 8.0 was used to conduct the descriptive statistics, modelling and sensitivity analysis. Jarque-bera test was used to determine skewness of the data, which is a measure of the deviation of datasets from their respective distribution [27]. In addition, augmented dicky fuller (ADF) test was employed for stationarity nature of the dataset. This tells us at what point are the variables simultaneously stationary and if the time series variables typical have a drift or deviation. Cumulative sum of recursive residual (CUSUM) and cumulative sum of squares of recursive residual (CUSUM squared) test was used to determine the structural stability of the coefficients of the variables. This structural stability is used to determine if a break will occur during the short and long run behaviour of the model to be generated. Furthermore, the Johansen cointegration test was also employed to ascertain the long run relationship of all the explanatory variables used in the development of the model while HAC (Newey-West) and Durbin Watson (DW) statistic was used to control for heteroscedasticity and auto-correlation respectively of the generated model.

3. Materials and methods

3.1. Pebbles as a rough material

Varying sizes of pebbles were sourced locally in Ota, Ogun State Nigeria. The pebbles were gathered and collected in a black polythene bags and transported to the Geotechnical laboratory in Covenant University where it was washed thrice with distilled water to expunged dirt's serving as contaminants. In addition, the pebbles were air dried and sieved into various particles size. The sieved pebbles were glued on a thick hard material and attached to the channel walls and the roughness coefficient were obtained using Eqs. (1) and (2), respectively [5]:

$$n = \frac{R^{\frac{2}{3}} S^{\frac{1}{2}}}{V} \tag{1}$$

$$K = n^{\frac{1}{6}} \tag{2}$$

3.2. Experimental measurement process for Tracer studies (TS) and dissolved oxygen (DO) measurements

Tracer Studies was achieved using common salt as the tracer. It is very affordable and non-toxic. This tracer act as a pollutant which is discharged into water bodies intentionally or accidentally, and the TS procedure used: variable distance-variable time method, is captured extensively in the literature by [4] and [1]. 0.03 kg of the common salt was initially mixed in 100 ml of water in a beaker and then turned into a volumetric flask for proper mixing and dilution. Furthermore, DO measurements were taken with Hanna Instrument Edge multi-meter (HI 2030) using a sensitive probe attached to the portable meter. Dissolved Oxygen measurement were monitored at the inlet and outlet respectively of the laboratory channel at the same time and the difference was used for modelling. Finally, regular probe calibration using the 1413 μS/cm and 12.33 mS/cm calibration standard solution manufactured by Hanna instruments was used for data accuracy.

3.3. Laboratory set-up

This experiment was carried out in the hydraulics laboratory situated in the Department of Civil Engineering, Covenant University, Ota, Ogun State. A flow channel with dimensions 4.0 m x 0.15 m x 0.175 m was used. The channel was fed with water from a source and was regulated manually to the desired flow conditions. The velocity of flow was obtained using a velocity meter and was altered three times. The side walls of the channel were coated with roughness of different sizes and arrangement (Table 1 and Plate 1) and clipped to make the materials stationary. The variables which were measured included: dispersion number, DO, velocity, depth—this was used to obtain Froude number and roughness coefficients—all measurement were obtained in duplicates for accuracy of datasets.

4. Results and discussion

Table 2 shows the descriptive statistics carried out on datasets. It showed that Dispersion number (δ), dissolved oxygen (DO), velocity (V), Froude number (Fr), Roughness (K) with mean values of 0.107 ± 0.05, 0.466 ± 0.065 mg/L, 0.241 ± 0.210 m/s, 0.025 ± 0.005 and 0.148 ± 0.119, respectively. Also, the normality of the variables—which shows the degree of deviation of the datasets, was conducted using Jarque-Bera test. The test indicated that all the dataset or observation with the exception of Froude number is symmetrical.

In addition, to determine inter-variable relationship and to identify any multi-collinear dataset that exist among the variables, correlation matrix was conducted. Table 3 shows that there is a strong positive relationship between velocity–roughness, (r = 0.875) while a strong relationship exist between Froude number–velocity and Froude number-roughness (k) having values of r = 0.69 and –0.94 respectively. For velocity-roughness relation, it is observed that as the roughness of the particle increased,

Table 1
Pebble sizes and their roughness coefficients

Sizes (mm)	K
Control	0.9312
6.3	1.0768
9.5	1.1064
12.5	1.1233
13.2	1.1167
13.2, 12.5, 9.5	1.1685
12.5, 13.2, 9.5	1.2024
9.5, 12.5, 6.3	1.1873
6.3, 9.5, 12.5	1.182

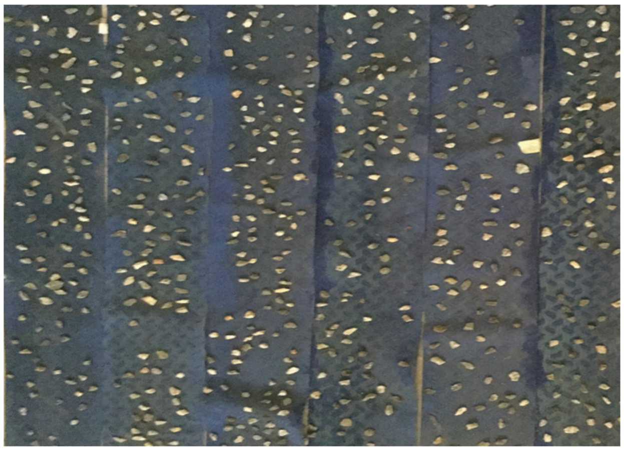

Fig. 1. Distribution of pebbles of varying sizes in the early experimental stage.

Table 2
Descriptive statistics of the explanatory variables

	Dispersion number (δ)	Roughness (K)	Froude number (Fr)	Dissolved oxygen (DO)	Velocity (V)
Mean	0.107	1.147	0.025	0.241	0.466
Median	0.117	1.123	0.026	0.210	0.460
Maximum	0.228	1.378	0.042	0.850	0.550
Minimum	0.007	0.931	0.017	–0.120	0.390
Std. Dev.	0.052	0.119	0.005	0.211	0.066
Skewness	–0.066	0.139	1.007	0.810	0.167
Kurtosis	2.770	2.005	4.505	3.100	1.564
Jarque-Bera	0.073	1.112	6.586	3.767	2.265
Probability	0.964	0.573	0.037	0.152	0.322
Sum	2.675	28.680	0.627	6.020	11.660
Sum Sq. Dev.	0.064	0.342	0.001	1.066	0.103
Observations	25	25	25	25	25

*null hypothesis: reject when $p < 0.05$ that the variable is normally distributed.

Table 3
Correlation statistics of all variables

	Velocity (V)	Roughness (K)	Froude number (Fr)	Dissolved oxygen (DO)	Dispersion number (d)
Velocity (V)	1.000	0.876	–0.687	–0.093	0.248
Roughness (K)	0.876	1.000	–0.942	0.113	0.170
Froude (Fr)	–0.687	–0.942	1.000	–0.251	–0.092
Dissolved Oxygen (DO)	–0.093	0.113	–0.251	1.000	–0.367
Dispersion number (δ)	0.248	0.170	–0.092	–0.367	1.000

Source: Author's computation achieved with e-Views 8.0 statistical software.

Table 4
Augmented Dickey Fuller summary test statistics of all variables

Variables	ADF test statistics	ADF critical values		Remark	Order of integration
		1% level	5% level		
Dispersion	–7.619	–3.753	–2.998	Stationary	I(1)
Velocity	–4.636	–3.753	–2.998	Stationary	I(1)
Froude	–6.004	–3.753	–2.998	Stationary	I(1)
DDO	–9.733	–3.753	–2.998	Stationary	I(1)
DK	–5.142	–3.753	–2.998	Stationary	I(1)

Source: Author's computation achieved with e-Views 8.0 statistical software.

Table 5
Model and sensitivity analysis using error correction method dependent variable: dispersion number

Variable	Coefficients	Standard error (S.E)	t-ratio	Probability	R^2	Adj. R^2	Durbin-Watson stat(DW)
C	–0.036	0.004	–8.729	0.000			
VELOCITY	–0.687	0.138	–4.992	0.000	0.977	0.960	2.106729
FROUDE	2.530	4.896	0.517	0.618			
DDO	–0.316	0.040	–7.802	0.000			
DK	0.694	0.162	4.278	0.002			
ECM	–0.465	0.060	–7.793	0.000			
AR(7)	–0.430	0.050	–8.679	0.000			
MA(6)	0.946	0.030	32.664	0.000			

Source: Author's computation achieved with e-Views 8.0 statistical software.

the velocity increased by 0.875. This value also reveals a strong presence of multi-collinearity in the model to be generated. Multi-collinearity implies that there is an exact relationship between parameters in our model i.e., since the inter-variable relationship is above 0.8, which reduces the trust placed on the R^2 values obtained from a typical regression model. In the same vein, a similar conclusion can be drawn from the Froude number-roughness relationship, except that the relationship is inverse.

From Table 5, it revealed that the relationship between dispersion number and velocity is strong and negative. This corroborates with the findings of [5] and [24] which also revealed an inverse relationship between the two parameter, i.e., an increase in velocity will bring about a decrease in dispersion coefficient. For example, when there is high velocity-peculiar in elevated gradient channels, the spread of pollutant will be reduced thereby producing pollutants of high concentration, which imply that the pollutants may not be degraded. Specifically, from this study, a 1-unit increase in velocity will result to a reduction in Dispersion coefficient by 0.687-unit. Likewise, this is supported by the *t*-statistics (t = –4.992; p < 0.05) which affirms that velocity is an important variable to be considered when issues on dispersion coefficient or dispersion number is to be modelled. The importance of velocity as a parameter to be measured has also been incorporated properly in the various method: variable distance constant time and variable distance variable time, used during tracer studies whereby tracer data are collected at different distances along the channel or river reach rather than only at the outlet [1].

Also, the co-efficient of Froude number was 2.53. This implies that there is a direct strong relationship between Froude and dispersion number. For every 1-unit increase in Froude number, there will be a 2.79-unit increase in dispersion coefficient. However, from the sensitivity analysis conducted with the aid of the *t*-value (t = –0.516; $p > 0.05$), it reveals that Froude number is not an important variable to be considered when modelling for dispersion co-efficient. On the other hand, with varying wall roughness, the co-efficient is 0.694. This connotes that there exists a positive relationship between dispersion coefficient and varying wall roughness. This may be due to the delay of tracers caused by roughness effect. When pollutants are retarded or stationary, the particles are held bound thereby promoting its spread. This is also in line with the study of [5], even though in that study the roughness assumptions irrespective of the materials considered during the experimental process were homogeneous. Furthermore, this study revealed that for every 1-unit decrease in wall roughness, there will be a corresponding decrease in the value of dispersion number by 0.694. Additionally, the *t*-ratio (t = –4.278; $p <$ 0.05) further indicates the importance of the parameter. It reveals that there is a need to include varying roughness as a pertinent variable when addressing dispersion number or its coefficient when modelling in channels and rivers. For dissolved oxygen (DO) as a variable, the co-efficient obtained is, –0.3156. This means that there is a low negative relationship between DO and dispersion co-efficient. Specifically, a 1-unit increase in dispersion co-efficient will cause DO to reduce by 0.3156. For instance, when pollutant are properly disperse, degradation by microorganism will increase owing to increase in surface area of pollutant, which in turn affect DO value. Furthermore, a decrease in the DO in streams or rivers may also result when there is high organic content, and this prevents oxygen-water interaction and decreases micro-organism degradation.

In the same vein, the t-statistics (t = –7.802; $p <$ 0.05) reveals that DO is a very important variable to be considered also during dispersion modelling. To mention, the model was adjusted with the error correction method (ECM), auto-regression (AR) and moving average (MA) catering for data heteroscedasticity. From the analysis, the ECM reveals that a period lag in ECM, i.e., (ECM (–1)) from the model generated shows a correction of short-run discrepancies of 46.5%. This is very significant as revealed by the *t*-ratio (t = –7.793; $p < 0.05$) . Interestingly, the R^2 = 0.98 and the probability-F statistics is 0.00001 which is less than 0.05. This implies that the combined influence of the variables featured in the model regarding predicting of dispersion co-efficient is well explained by the model.

The Durbin-Watson statistics reveals the auto-correlation of the error term, and it exists when its value lies outside the limits 1.8–2.2. Therefore, from the analysis, the Durbin-Watson statistics was found to be 2.1 which is an indication of the absence of auto correlation, and giving further confidence to the regression model generated. Likewise, to ascertain the stability of the variables, parameter stability test was conducted (see Figs. 2 and 3) using the CUSUM and the CUSUM square test. The graphs reveal that over time, the co-efficient used as well as the parameters are stable. This is concluded as the blue lines remained within the boundaries of the red lines thereby supporting the validity of the coefficients-parameter

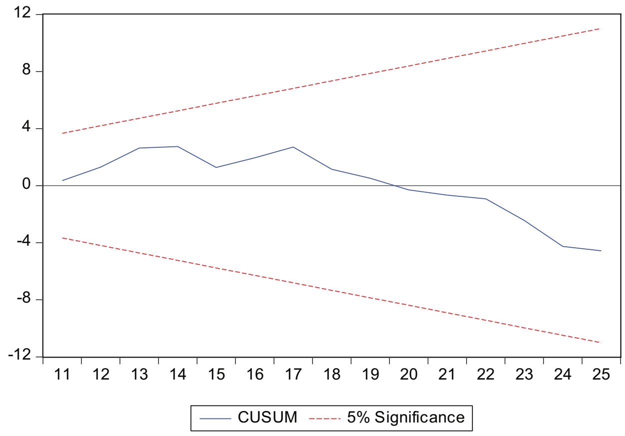

Fig. 2. Parameter structural stability test for coefficients (CUSUM).

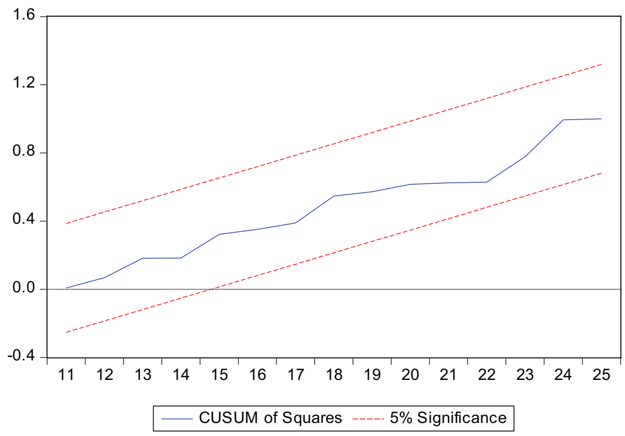

Fig. 3. Parameter structural stability test for coefficients (CUSUM SQ).

relationship. The equation representing the variables used in the analyses is shown in Eq. (3):

$$D(DDispersion)_t = \beta_o + \beta_{1i}\sum_{i=0}^{n} D(DVelocity)_t + \beta_{2i}\sum_{i=0}^{n} D(DFroude)_t + \beta_{3i}\sum_{i=0}^{n} D(DDO)_t + \beta_{4i}\sum_{i=0}^{n} D(DK)_t + ECM_t(-1) \quad (3)$$

where $i = 1, 2, 3\ldots n$. Also,

β_o = constant or intercept
β_{1i} = coefficient of velocity (m/s)
β_{2i} = coefficient of Frounde number
β_{3i} = coefficient of DO (mg/l)
β_{4i} = coefficient of roughness (K)

Also, cointegration test of the dataset was conducted using the Johansen cointegration test to determine the long run relationship. It indicated that there are 5 cointegration variables significant at the 1% level, therefore, the variables over time will not generate contrary interpretation. This is

Table 6a
Johansen cointegration test result

Sample (adjusted): 3 24
Included observations: 22 after adjustments
Trend assumption: Linear deterministic trend
Series: Dispersion velocity Froude DDO DK
Lags interval (in first differences): 1 to 1
Unrestricted cointegration rank test (Trace)

Hypothesized No. of CE (s)	Eigen value	Trace statistic	0.05 Critical value	Prob.**
None*	0.850613	116.7855	69.81889	0.0000
At most 1*	0.807780	74.95877	47.85613	0.0000
At most 2*	0.572869	38.67827	29.79707	0.0037
At most 3*	0.381441	19.96367	15.49471	0.0099
At most 4*	0.347586	9.395678	3.841466	0.0022

Trace test indicates 5 cointegrating Eqn(s) at the 0.05 level; * denotes rejection of the hypothesis at the 0.05 level;
*MacKinnon-Haug-Michelis (1999) *p*-values.

Table 6b
Johansen cointegration test result

Unrestricted cointegration rank test (Maximum Eigen value)

Hypothesized No. of CE (s)	Eigen value	Max-Eigen statistic	0.05 Critical value	Prob.*
None*	0.850613	41.82672	33.87687	0.0046
At most 1*	0.807780	36.28050	27.58434	0.0030
At most 2	0.572869	18.71461	21.13162	0.1054
At most 3	0.381441	10.56799	14.26460	0.1772
At most 4*	0.347586	9.395678	3.841466	0.0022

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level;* denotes rejection of the hypothesis at the 0.05 level;
*MacKinnon-Haug-Michelis (1999) p-values.

Table 7
Breusch-Godfrey serial correlation LM test

F-statistic	0.132984	Prob. F(1,8)	0.7248
Obs*R-squared	0.248150	Prob. Chi-Square(1)	0.6184

*null hypothesis: accept when $p > 0.05$ and conclude that no auto-correlation.

Table 8
Heteroscedasticity test: Breusch-Pagan-Godfrey

F-statistic	0.109970	Prob. F(5,11)	0.9877
Obs*R-squared	0.809316	Prob. Chi-Square(5)	0.9764
Scaled explained SS	0.165171	Prob. Chi-Square(5)	0.9994

*null hypothesis: accept when $p > 0.05$ and conclude that there is no Heteroscedasticity.

shown in Table 6a and 6b. Lastly, heteroscedasticity and auto-correlation test was carried out using the Breusch-Pagan-Godfrey (Table 8) and Breusch-Godfrey Serial Correlation LM test (Table 7). The value from both test showed that there are no heteroscedasticity and auto-correlation in the generated model, i.e., $p > 0.05$, and bolsters the auto-correlation result previously obtained from the Durbin-Watson statistics value (Table 5) and conclude that there is no heteroscedasticity and auto-correlation present in the model generated.

5. Conclusion

In a bid to improve the accuracy of dispersion coefficient estimation in channels or rivers, the possible effect of varying roughness on dispersion coefficient was considered. Modelling and sensitivity analysis were carried out statistically to determine the relationships of the independent variables—velocity, Froude, dissolved oxygen and roughness coefficient on the dispersion coefficient, and their statistical significance. This will assist researchers and experts to better understand the factors affecting the spread of pollutants. From the study, apart from velocity, which have been hitherto established, DO and roughness coefficient have shown to be important factors in the estimation of dispersion coefficient with coefficient, t-values and probability of –0.3156; $t = –7.802$; $p = 0.0000$ and 0.694; $t = 4.278$; $p = 0.0021$ hitherto have not been included as essential parameters for the modelling of dispersion coefficient. Finally, the R^2 = 0.977 confirms that the explanatory variables considered in this study, for the estimation of the dispersion coefficient are appropriate. Future work should include wall and bottom roughness and how dispersion coefficient is affected using other tracer studies techniques to demonstrate the consistency of this findings.

Acknowledgment

The Authors thank the Management of Covenant University for the enabling environment, facilities and support towards actualising this study. Also, we thank the anonymous reviewers for their constructive contributions.

Symbols

ADF	— Augmented Dickey Fuller
AR	— Auto-regression
C.E	— Cointegration equation
CUSUM	— Cumulative sum of recursive residual
CUSUM SQD	— Cumulative Sum of Squared Recursive Residual
DW	— Durbin-Watson statistics
D(Velocity)	— Differential of velocity coefficients
D(Froude)	— Differential of Froude number coefficients
D(DO)	— Differential of dissolved oxygen coefficients
D(K)	— Differential of roughness coefficients
ECM	— Error correction methodology or model
I(1)	— Integration order (first order)
MA	— Moving average
r	— Coefficient of correlation
R^2	— Coefficient of determination
S.D.	— Standard deviation
S.E.	— Standard error
t	— t-statistics

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