JPMTR-2306
DOI 10.14622/JPMTR-2306
UDC 681.621.25:681.621.5-035.67-026.55

Original scientific paper | 179
Received: 2023-03-31
Accepted: 2023-09-24

Prediction of offset ink film thickness using machine learning

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Abstract

The wet film thickness of printing ink in offset printing process is an important parameter which is related with the print quality and cost. In this paper, the prediction of ink film thickness in offset printing based on machine learning has been proposed. For measurement and prediction of wet ink film thickness in offset process, an experimental inking model is designed and used to show the effect of various factors like machine speed, run time, ink color, ambient temperature, and relative humidity on it. The machine learning based prediction models can provide very close approximation of the accurate information about the control parameters so that the print technician could make a good setting work during real-time production process. With the help of this, the technician can make a good decision in the setting of control parameters for ink thickness based on this predictor. The results show that the prediction models can provide about 95 % accuracy in predicting the ink film thickness. Thus, the prediction system not only can help technicians and greatly improve their production efficiency, but also can save the cost of production.

Keywords: offset printing, prediction models, support vector regression, random forest regression

1. Introduction

Offset printing industries face lots of problems because of variations in ambient conditions and therefore, it is necessary to maintain a standard ambient condition of machine surroundings. The offset inks of all colors are also sensitive to temperature and relative humidity. In offset printing ink flows from the ink container to the inking system through the annular space between a series of rollers and for this co-axial cylinder viscometer can be chosen as a model where flow of non-Newtonian fluids is in between two concentric cylinders. But in offset printing machines, the rollers are not concentric where the radius of the outer cylinder or roller is treated as infinity. Rollers in the inking system are mainly rotated via gears and a wet ink film is formed by hydrodynamic effect generated from relative motions of the contacting rollers. The contact surface is nearly non-heavy load linear contact friction, so it may be considered as generalized elastohydrodynamic lubrication. Thus, it may be predicted that there is not a large difference between the ink film thickness and the film thickness of corresponding hydrodynamic lubrication. (Liu, Li and Lu, 2016)

The modern offset presses need a standardized model for flow of ink through the inking system of offset machines, for which optimum ambient conditions inside the machine room are required. Moreover, the inking rollers will be getting heated with machine run time and speed due to the friction, which may lead to the change in wet ink film thickness. To compensate this effect and achieve correct ink film thickness, the process parameters have to be calibrated each time, which is tedious and time consuming.

Prediction of optimum wet ink film thickness is a matter of concern, which is evident from various research works. An experimental study (Hsieh, 1993) conducted in laboratory showed an association between the ink film thickness and its splitting forces. The development of the ink key presetting system has been studied (Chu and Seymour, 1997), which could analytically preset ink keys and ratchets to shorten the make ready time. Estimation of ink tack in offset printing had been investigated (Gujjari, et al., 2006) by examining the printing speed and ink weight for different newsprint. Variations of ink thickness had been studied (Hersch, et al., 2009) by using spectral reflectance's prediction model. Elastic deformation of rubber ink roller and characteristics of ink flow through two ink rollers had been studied (Su, et al., 2012) under different conditions to determine the rate of ink transfer. Reynolds equation for ink transfer in offset inking system had been deducted (Liu, Li and Lu., 2016) on the basis of electro-hydrodynamic lubrication theory, and the effect of ink transfer on printing speed and roller gap was also analyzed.

Machine learning (Chopra and Khurana, 2023) is an emerging field nowadays. Due to significant development in hardware and software along with interfacing possibilities machine learning has become a popular tool for the prediction, classification and identification in diverse engineering problems. It has been used in automotive (Jain, et al., 2022), food engineering (Jiménez-Carvelo, et al., 2022), structural engineering (Thai, 2022), financial sectors (Rakshit, Clement and Vajjhala, 2022) and in almost all the major areas. It has been used in printing researches but recent literatures are mostly in the field of 3D printing and additive manufacturing (Zolfagharian, Bodaghi and Le Doigou, 2022). However, considering the huge reported literature of its applications in all fields other than printing and allied domains motivates towards exploring the scope of the work presented in this paper. This paper focuses on the possibilities of applying machine learning based prediction models to predict the ink film thickness in offset printing machines while major parameters of ambient press conditions are varied.

In this present investigation, a novel methodology of prediction of wet ink film thickness has been developed on the basis of variation of ink film thickness with respect to different speeds and run time for different ambient conditions using machine learning regression algorithms. This will allow proper standardization of ink film thickness and can be implemented in offset printing process.

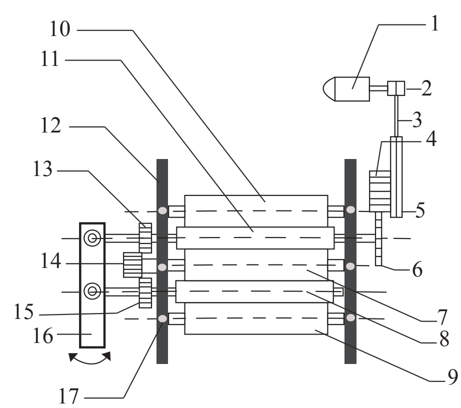
2. Materials and methods

A prototype of an inking roller arrangement that simulates the actual inking system of offset printing machines has been developed. The commercially available offset inks of process colors, namely, cyan (C), magenta (M), yellow (Y), and black (K) were used for measurement and prediction of purpose. Among different prediction models, two popular ones, namely, support vector regressor (SVR) (Steinwart and Christmann, 2008) and random forest regressor (RFR) (Breiman, et al., 2017) algorithms have been adopted here due to their simplicity and proven potential. A detailed dependency analysis between ink film thickness and different major parameters of ambient conditions that affect ink film thickness has been also presented towards understanding the degree of non-linearity in correlation. The results have been evaluated using three important evaluation metrics, namely residual plots, R^2 values, and mean squared error (MSE) (Freund, Wilson and Sa, 2006).

2.1 Experimental procedure

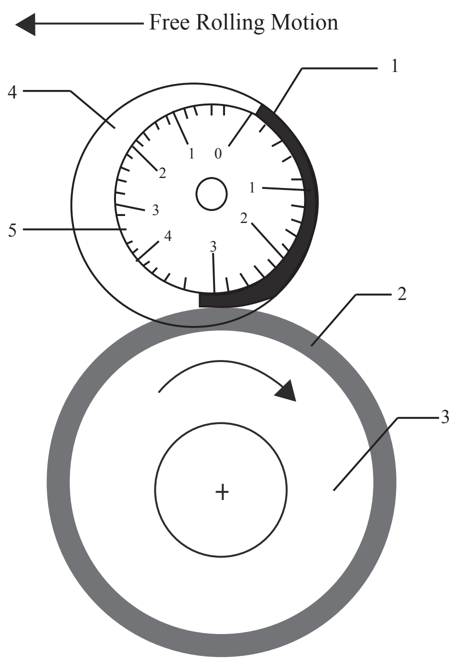
The experiments were performed on inking rollers, which are an integral part of an inking system in an offset printing machine. The experimental model of inking rollers was custom-designed and manufactured as shown in Figure 1. The model consists of two hard rollers driven by gears and a pulley connected to a DC motor by a V-belt. Hard rollers and soft rollers are arranged alternately and three soft rollers are driven by friction with the hard rollers. The hard rollers have both rotating motion and sliding motion, while the soft rollers have only rotating motion. The sliding motion of hard rollers helps to distribute the ink evenly throughout the whole length of the rollers.

The thickness of ink coating of different colors on rollers was measured at varying time and speed each at different ambient conditions. The ink thickness was measured systematically using a wet film thickness gauge, which has a combination of three rolling disc sections. The two outer discs are exactly the same diameter, whereas the middle disc is smaller and eccentric to the outer two discs. As the gauge is rolled through a wet deposition of ink, the eccentric middle disc would only pick up the ink from the inked rollers, as illustrated in Figure 2. Wet and dry bulb thermometers have been used for the measurement of ambient temperature and relative humidity.



1. DC motor	7. Soft roller 2	13. Gear 3
2. Motor pulley	8. Hard roller 1	14. Gear 4
3. Rubber V-belt	9. Soft roller 1	15. Gear 5
4. Gear 1	10. Soft roller 3	16. Oscillating lever
5. Gear pulley	11. Hard roller 2	17. Adjusting screws
6. Gear 2	12. Supporting frame	

Figure 1: The ink roller model used for the experiment



1. Ink pickup on measuring disk
2. Ink
3. Soft roller
4. Eccentric measuring disk
5. Two concentric support disks

Figure 2: Ink thickness measuring gauge

2.2 Materials

The constituents of inks greatly affect the different parameters under consideration in this work. The general data on the constituents of the commercial offset inks used for experiments have been consolidated in Table 1 (Leach, et al., 1993). The inks were supplied by DIC India Limited, Kolkata, India. Experiments were conducted on the custom-made model of inking rollers (shown in Figure 1) by using these inks. The size of the roller was limited, hence limited amount of ink of 4.0 g/m^2 was used every time with a variation of about 0.1 g/m^2 for each color. After the ink was evenly distributed through all the rollers with the help of an oscillating lever attached to the hard rollers as shown in Figure 1, wet ink film thickness was measured on different sections of both soft rollers 1 and 3. The speed of the motor was modulated by varying the voltage of the supply current and measurements were conducted using the instrument called a tachometer. The process was continued until the maximum speed was reached.

2.3 Regression modeling to characterize ink film thickness

The choice of SVR and RFR regressors among many such regressors is driven by their computational simplicity, faster prediction and considerable accuracy in predicting non-linear dataset. It can also be noted that by principle these two algorithms work in a totally different manner. The SVR is a kernel-based operation to address the non-linearity in the data using support vectors while RFR is one of the most popular ensemble learning mechanisms that predicts based on the probability values resulting from different decision trees in the model. Brief discussions about these two supervised machine learning algorithms have been presented here for ready reference. The data as collected by the previously discussed method were subjected to both the models and the prediction abilities of the individual models have been assessed.

The implementation of the prediction models has been made with a train:validation:test data partitioning with 60:20:20 ratios. That means with 60 % of entire data the models were trained; 20 % of the entire dataset was used for validation, i.e. tuning the parameters, and 20 % for testing the generalization potential. A good generalization potential helps to avoid two important drawbacks of machine learning algorithms called over-fitting and under-fitting. In both cases the models can perform well with the training data but fail to perform equally in case of unknown data. The implementations are realized in a Python environment using Anaconda Spyder® and scikitlearn® libraries in the Windows® PC

Table 1: Generic ink formulation of cyan, magenta, yellow, and black (Leach, et al., 1993)

Type	Cyan	Magenta	Yellow	Black
Pigment	Lionol Blue FG-7330 20.0 %	Rubine L5B 01 VP 2746 18.3 %	Yellow CI number 12/ Lionol Yellow GRO 26.7 %	Regal 99R carbon black 12.0 %
Polyester alkyd resin	40.0 %	40.0 %	33.3 %	45.0 %
Anti-fly paste	3.0 %	3.0 %	3.0 %	3.0 %
Solvent	14.0 %	15.7 %	14.0 %	17.0 %
Melamine formaldehyde resin	12.0 %	12.0 %	12.0 %	12.0 %
Catalyst	2.0 %	2.0 %	2.0 %	2.0 %
Lubricating oil	7.0 %	7.0 %	7.0 %	7.0 %
Stabilizer	2.0 %	2.0 %	2.0 %	2.0 %

platform. In both the cases the prediction of ink film thicknesses on the rollers has been made separately.

2.3.1 Support vector regression

The SVR generates different hyperplanes based on the calculated support vectors and optimizes to find the solution where these hyperplanes are separated to the maximum extent. The space of the hyperplane depends on the problem dimension. Being a supervised machine learning algorithm SVR conceptually constructs a tube around each of the hyperplanes by minimizing the prediction error, which fundamentally finds the distance between the expected value and the predicted value in order to achieve that SVR eventually narrows down the tube and approaches towards flatness. The flatness of the tube can be assessed by Equation [1] where M is the order of polynomial function, w is the normal vector to the hyperplane surface and both are real-valued. The order of polynomials depends on the type of problem and in our case order of 3 was found to be optimal.

$$f(x,w) = \sum_{i=1}^{M} w_i\, x^i \qquad [1]$$

In the case the data is not linearly separable, like in our case, a kernel mapping is used to map the data in higher dimensional space, which results higher prediction accuracy as well. In our case radial basis function (RBF) kernel has been used for that reason. The SVR also adopts a penalization parameter for predictions that are far from the expected value and it is measured in terms of width of the tube. Interested readers can read the details of SVR dynamics in the publication by Awad and Khanna (2015).

2.3.2 Random forest regression

Random forest is a supervised machine learning algorithm, which is popular due to many reasons like fast training and prediction, lesser number of tuning parameters and considerable potential to handle large dimensional problems with appreciable generalization power. It can be used in both classification and regression analysis. In our case the prediction of continuous data is needed hence random forest repressor has been adopted.

It is an ensemble learning process where the term 'forest' resembles number of decision trees (DTs). Each tree is associated with a collection of random variables that is represented as a vector X and the dimension p of X depends on the dimension of the problem as presented in Equation [2].

$$X = \left(X_1, X_2, \dots, X_p\right)^T \qquad [2]$$

The RFR by means of its mathematical optimization process finds a prediction function $f(x)$ and each tree provides a vector of predicted values Y using $f(x)$. The prediction function is defined using a loss function which is most commonly the squared error and the algorithm iterates to minimize the estimated loss value $E_{XY}(L(Y,f(x)))$. Considering the ensemble learning phenomenon for regression the f is constructed as Equation [3] where h_j represents individual tree (alternatively called the base learner) and j is the index of tree. However, in case of classification a 'voting' mechanism is adopted. Interested readers can read the details of the algorithm in the publication by Cutler, Cutler and Stevens (2012). The parameter settings of SVR and RFR for the present study are given in Table 2.

$$f(x) = \frac{1}{J}\sum_{j=1}^{J} h_j\,(x) \qquad [3]$$

Table 2: Parameter settings for prediction models

SVR	RFR
Kernel – Radial basis function (RBF)	Bootstrap – True
	Optimization criteria – MSE
Epsilon – 0.1	Minimum sample leaf – 1
Tolerance – 0.001	Minimum sample split – 2
Verbose – False	Number of trees – 2000
Cache size – 200	Random state – 0
	Verbose – 0

3. Results

The dataset used in this work had 6 columns, i.e. color, the run time (min), speed of rollers (rpm), average ink film thickness (µm), ambient temperature (°C), and relative humidity (%). The nature of the data correlation and degree of non-linearity were studied using scatter plots as shown in Figure 3. The accuracies of the individual models with different cases have been shown using percentage residual plots and R^2 values. Some of the prediction vs. actual plots for SVR and RFR are shown in Figures 4 and 5, respectively.

Residual plots are another important visual representation to see the coherence of predicted values to the actual values. It also shows the resulting outliers, which in turn can help to judge the potential of the model. The residual plots for SVR and RFR are shown in Figures 6 and 7, respectively.

The result of 10-fold cross-validation is shown in Table 3. The average prediction accuracy and standard deviation values for both the prediction models have been included in the table as well. The 10-fold cross-validation is one of the most popular metrics,

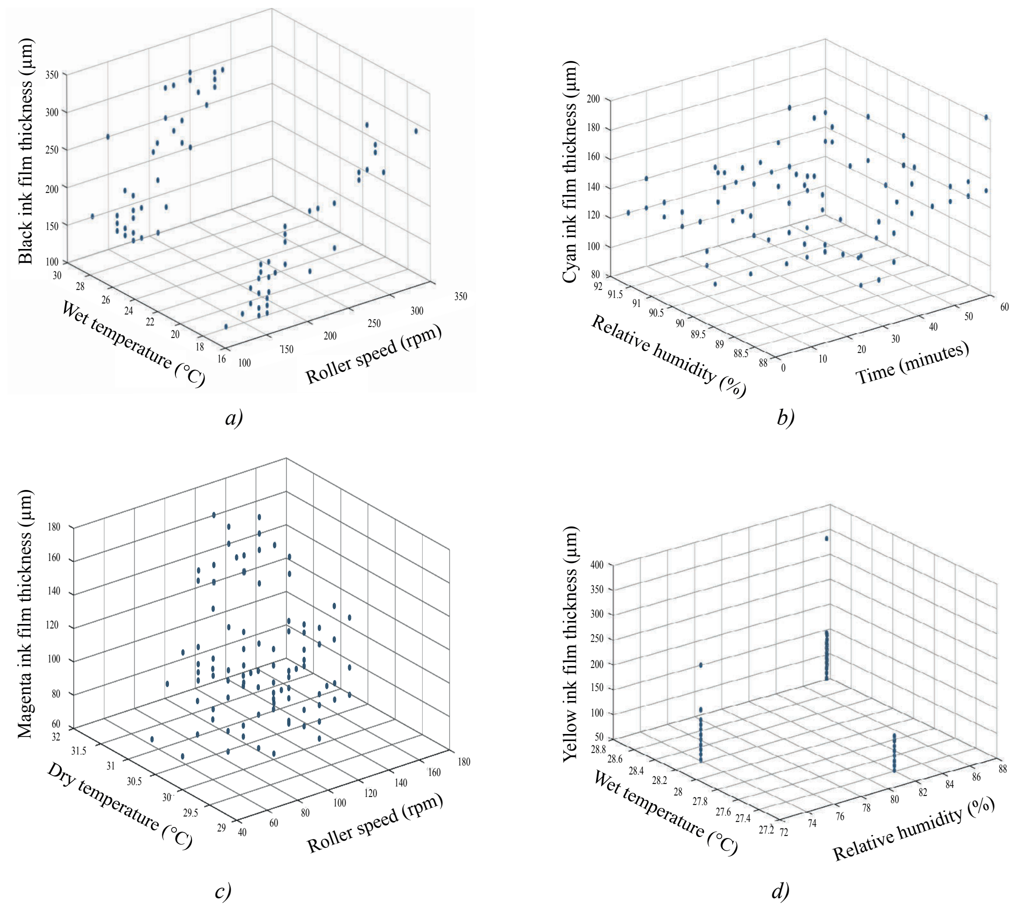


Figure 3: Examples of scatter plots of varying pattern for (a) black ink thicknesses with roller speed and wet temperature of environment, (b) cyan ink thicknesses with roller moving time and relative humidity of environment, (c) magenta ink film thicknesses with roller speed and dry temperature of environment, and (d) yellow ink thicknesses with relative humidity and wet temperature of environment

which folds the data in a way that at every run 90 % of the validation data is subjected as a training set and the rest 10 % as the test set. In this way, every data gets included in the train and test set at least once.

Table 3: The cross validation and overall accuracy of the regressors

Test	SVR	RFR
Fold 1	87.93	82.87
Fold 2	82.87	89.59
Fold 3	89.59	95.53
Fold 4	95.36	96.19
Fold 5	96.19	93.02
Fold 6	93.02	92.87
Fold 7	82.87	94.27
Fold 8	94.27	98.80
Fold 9	88.80	88.20
Fold 10	91.20	97.32
Average accuracy	90.21	92.87
Standard deviation	±4.78	±4.80

As it can be seen RFR provides improved consistency than SVR. However, in both cases, the average overall accuracy is in the tune of more than 90 %.

Hence, the prediction model can be considered as a potential addition to the existing manual and time-consuming systems of ink film thickness measurement techniques.

Table 4 provides the R^2 and MSE values for the predictors under consideration. These two are also important metrics to access the potential of the prediction models. Higher R^2 values and lower MSE values reflect better prediction possibilities.

Table 4: Comparison of prediction models in terms of R^2 and MSE

Metric	SVR	RFR
R^2	0.8923	0.9474
MSE	0.0971	0.0836

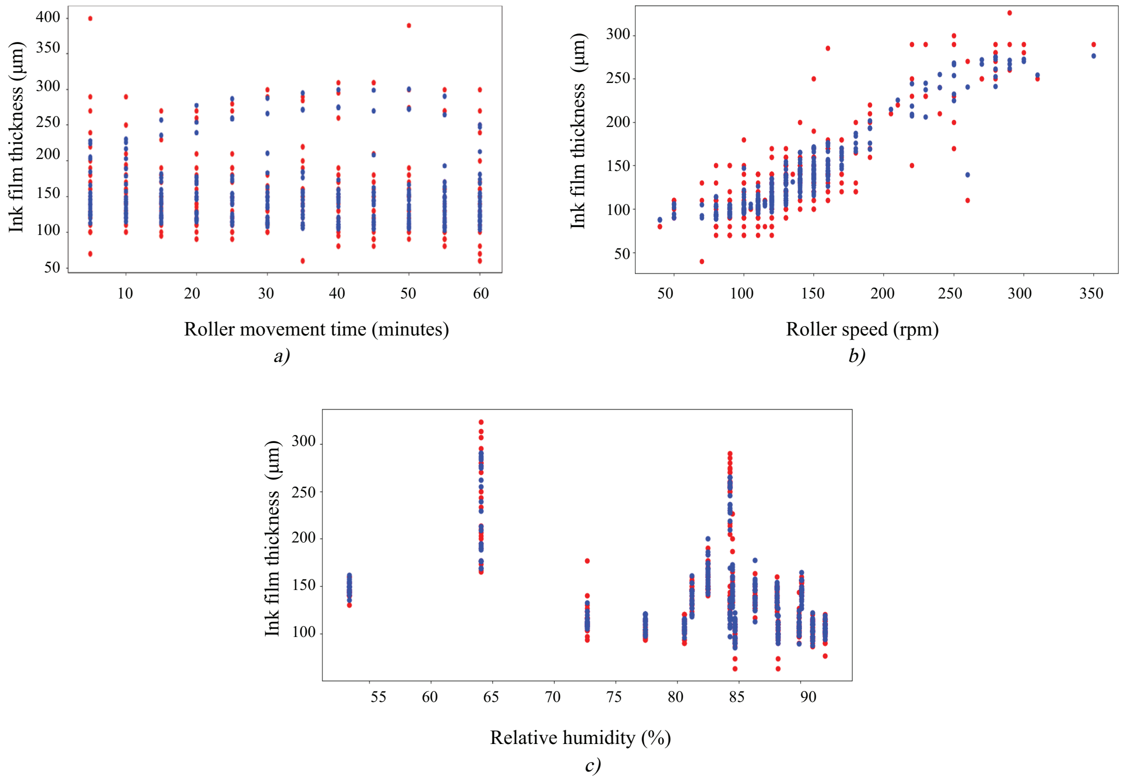


Figure 4: Prediction vs. actual ink film thickness against (a) roller movement time, (b) against roller speed, and (c) relative humidity using SVR; blue and red points represent actual and predicted values, respectively

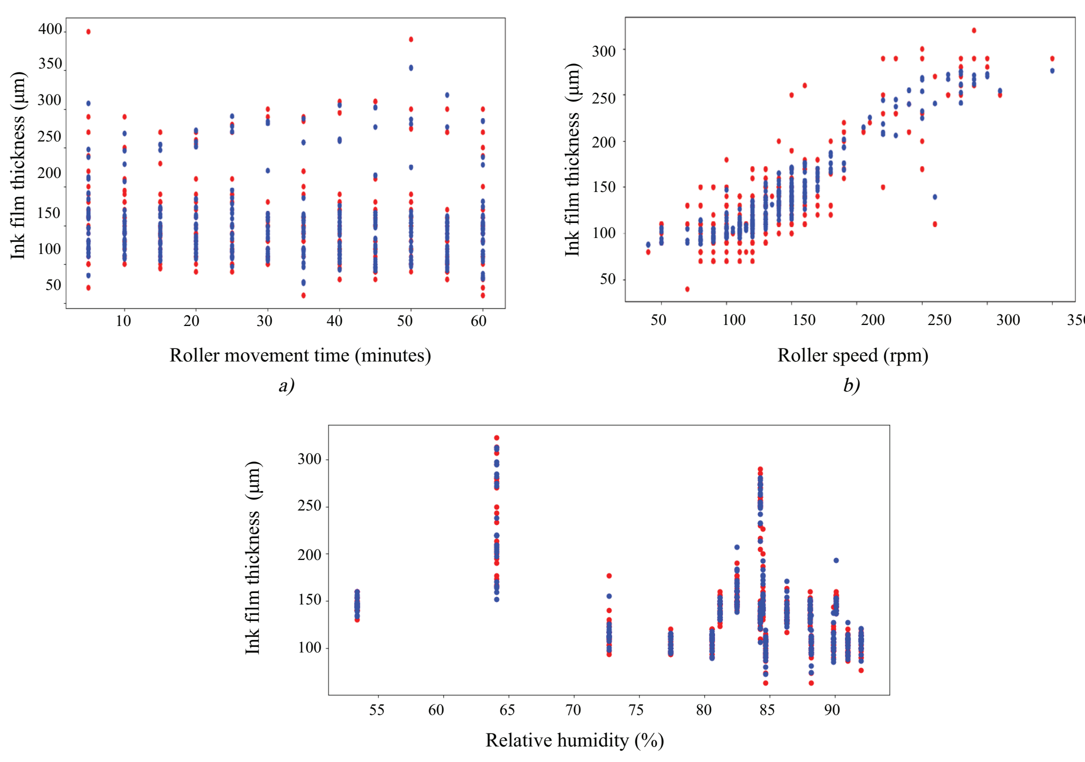


Figure 5: Prediction vs. actual ink film thickness against (a) roller movement time, (b) against roller speed, and (c) relative humidity using RFR; blue and red points represent actual and predicted values, respectively

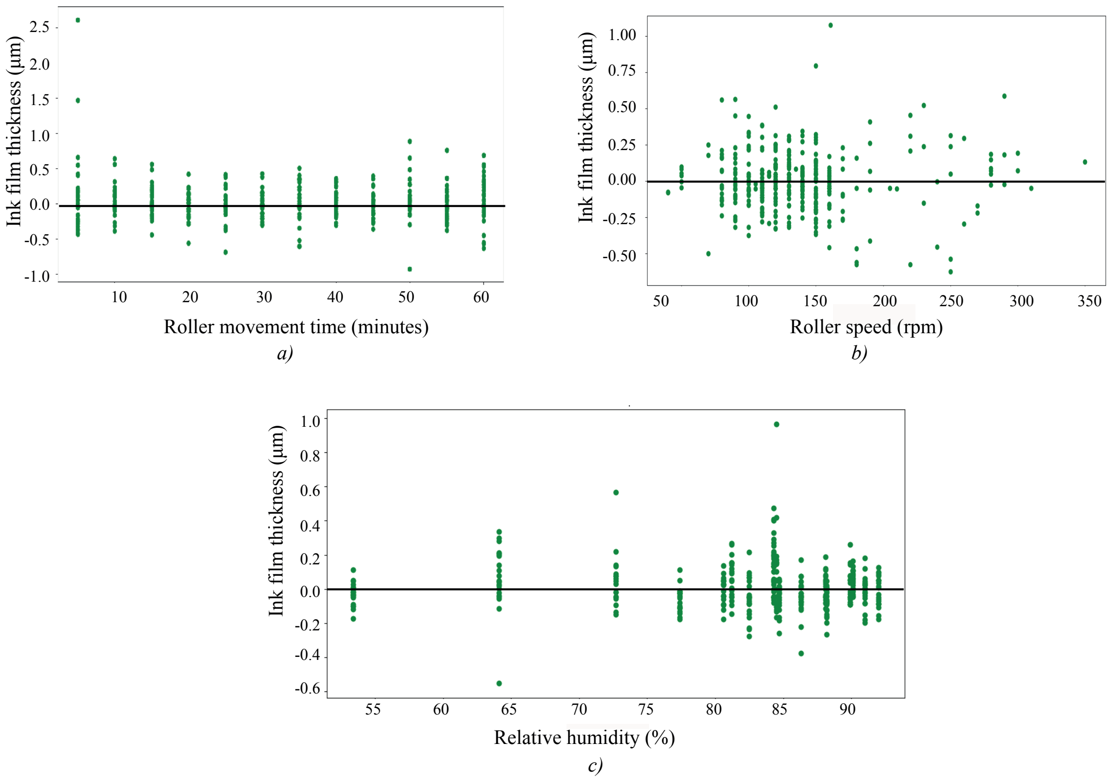


Figure 6: Residual plots for prediction results using SVR in the case of ink film thickness against (a) roller movement time, (b) against roller speed, and (c) relative humidity

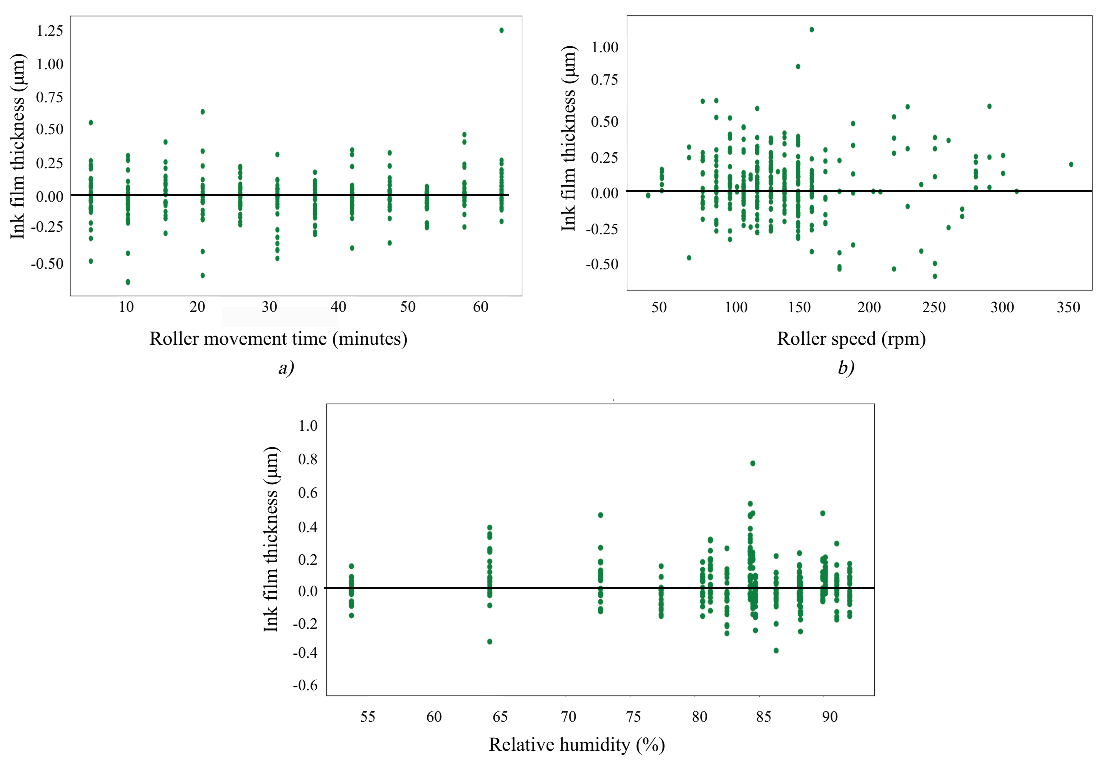


Figure 7: Residual plots for prediction results using RFR in the case of ink film thickness against (a) roller movement time, (b) against roller speed, and (c) relative humidity

4. Discussions

Figure 3 clearly shows that wet ink film thickness is well dependent on the factors under consideration. Even if the conditions remain consistent the ink film thickness changes with the ink color as well. The plots have also revealed a considerable degree of non-linearity. This motivates towards development of the regression model which can predict the ink film thickness in the rollers of the experimental model. The plots also show that RFR can predict more accurately compared to SVR. As in most of the cases the actual and predicted values (blue and red points) are overlapping in case RFR.

The residual plots in Figures 6 and 7 show that SVR can predict closely to the actual data points in most of the cases and also in terms of residual plots the points are closer to the value 0 (as shown by the black line in the plots). Also, the data spread across both sides of the zero line shows the unbiased of the data. The total number of outliers in all the residual plots is also considerably low to the tune of 2 % of the entire test dataset. The residual plots also indicate better prediction by RFR in terms of closeness to the reference line and a lower number of outliers compared to SVR. It can be also noted that the performance of SVR and RFR are similar for most of the samples hence the plot characteristics are quite the same. However residual plots show smaller deviations from the reference line and lower degrees of outliers in the case of RFR. Hence RFR can be considered as a better predictor than SVR in this study which is further reflected in Tables 3 and 4.

In terms of 10-fold cross-validation results it can be inferred that both models show considerable consistency with low standard deviation values. The parameter settings for such fold have been used in the presented results. The average accuracy in both cases is more than 90 % while RFR has shown better accuracy. It can also be observed that in some folds for both the regression models, the accuracy has crossed 95 %.

Finally, it can be seen that in terms of R^2 both the predictors result in nearly 90 % accuracy while the accuracy with RFR is higher. The same is reflected with MSE values where RFR has resulted in less. Considering the lower MSE values both the models have shown promising prediction potential in our case. Nevertheless, considering both R^2 and MSE, RFR is a better predictor for the presented work.

5. Conclusion

In this study, experiments have been carried out simulating real production conditions. The experimental results demonstrate that there is a correlation between ink film thickness and machine run time and speed for different ambient conditions. The analytics of the results obtained show some significant aspects, which may be useful for standardization. The analysis of the regression model shows that at a constant speed, as the relative humidity decreased and temperature increased, the ink film thickness increased. The ink film thickness decreased when the relative humidity increased and temperature decreased. When speed was varied, the ink film thickness increased up to a point with the rise in relative humidity and thereafter decreased with a further increase in relative humidity. It is concluded that by adopting the proposed regression model for assessing the wet ink film thickness at varying machine run time and speed, proper standardization of ink film thickness can be implemented in the offset printing process.

The study also reveals that both SVR and RFR regression models can perform competitively for accurate prediction of ink film thickness. The present investigation undoubtedly confirms that this regression model for effective measurement of ink thickness works accurately well in offset printing.

From this study, it is evident that offset printing process has a scope of mechanism to adjust the ink film thickness at varying time and speed for different ambient conditions. This approach can also be extended to find out the correlation between ink film thickness and roller contact pressure along with ink film thickness (i.e. the gap between rollers) and the size of the rollers. Also, the effect of the damping solution along with the proper ink deposition on the impression cylinder needs to be studied further for optimum ink-water balance as in real offset printing conditions. The experimentations with different other prediction models can also be performed in future research.

This work can as well be extended toward the hardware implementation of automated controls in printing machines. Considering the findings and future scopes the proposed approach may be considered as an important dimension to the emerging area of optimization and prediction of ink thickness in offset printing process.

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