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Transport and Telecommunication, 2018, volume 19, no. 4, 335–345
Transport and Telecommunication Institute, Lomonosova 1, Riga, LV-1019, Latvia
DOI 10.2478/ttj-2018-0028

ANALYSIS OF CROWD FLOW PARAMETERS USING ARTIFICIAL NEURAL NETWORK

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Research scientists have been developing mathematical tools to detect objects, recognize objects and actions, and discover behaviours and events to human abilities. In all these efforts, the understanding of human actions is of a special interest for both application and research purposes. In this study, crowd flow parameters are analysed by considering linear and non linear relationships between stream flow parameters using conventional and soft computing approach. Deterministics models like Greenshield and Underwood were applied in the study to describe flow characteristics. A non-linear model based on Artificial Neural Network (ANN) approach is also used to build a relationship between different crowd flow parameters and compared with the other deterministic models. ANN model gave good results based on accuracy measurement to deterministic models because of their self-processing and intelligent behaviour. Mean absolute error (MAE) and root mean square error (RMSE) values for the best fitted ANN model are less than those for the other models. ANN model gives better performance in fitness of model and future prediction of flow parameters.

Keywords: ANN; deterministic models; Greenshield; Macroscopic flow diagram; MAE; RMSE

1. Introduction

Large political rallies, religious gatherings, and ceremonies, which involve large groups of people pose significant challenges for officials in terms of monitoring, security, and organization. In large gatherings, the security of the event is of the highest importance. In dense crowds, any abnormal behaviour or incident would lead to a stampede because of human interactions (Farkas et al. 2000). For example, the annual Muslim Hajj in Mecca, which is attended by millions of pilgrims, has increasingly suffered from stampedes, even as authorities have constructed new walkways and instituted other traffic controls to prevent them. Similar incidents have reported in India during Hindu religious gatherings (Moonen and Forstner, 2011). To improve the coordination of the crowds and to facilitate the flow of the people in public spaces, the transportation researchers are increasingly interested in upgrading urban designs to adapt them to public needs and habits. A crowd is a sizeable number of people (pedestrians) gathered at a specific location for a measurable time period, with common goals and displaying common behaviours (Musse and Thalmann, 1997). Analyses of crowd flow characteristics are required at crowded locations for the easy movement without a jam. Crowd characteristics can be defined based on macroscopic and microscopic methods. A. D. May (1967) described that the modelling phenomenon between vehicles and pedestrians are separated by only numerical values and units. Fruin J.J (1971) observed pedestrian flow characteristics based on macroscopic approach. Pedestrian flow characteristics analysed by using three parameters, namely speed (U), density (k), and flow (Q). According to traffic flow theory, relationships among three principle variables are used to derive the crowd flow characteristics (speed–density, flow– density and speed–flow). The main objective of this study is to observe traditional relationships between crowd flow parameters based on field data by considering deterministic and artificial neural network (ANN) approaches. Crowd flow parameters such as the jam density, free flow speed were derived based on deterministic models to describe crowd characteristics. Greenshields (1935) proposed a linear relationship between speed and density, whereas Underwood R.T. (1961) proposed an exponential relationship between speed and density. The deterministic models explain average system behaviour considering physical laws.

In this study, ANN is used to analyse the relationship between crowd flow parameters. Artificial Neural Network (ANN) concept was initially proposed by Warren McCulloch and Walter Pitts in 1943. Sharma *et al*. (2005) developed vehicular pollution models using ANN to predict air pollution concentration in an urban environment. Murat Y.S. and Baskan O. (2006) developed vehicle delay estimation model using ANN approach. Zhao L. and Thorpe C.E. (2000) developed pedestrian tracking system and flow prediction model in the pedestrian study area using ANN approach. ANN model is proposed for modelling crowd flow based on observed pattern of field data. ANN model is validated by comparing with other deterministic models by performing various statistical analyses like route mean square error (RMSE) and mean absolute error (MAE).

2. Literature review

Object detection and tracking is very important because of wide range applications in human activity monitoring, public safety in places like banks, shopping malls, private places etc. In this paper, density was measured by object detection technique and speed is measured by object tracking technique. Many mathematical models have been proposed in the literature to represent the relation between speed-density-flow. Some classical and commonly used deterministic models are Greenshields and Underwood. Some researchers developed nonlinear models to represent the actual relation between speed– density-flow. In this study, ANN model is used to develop a macroscopic flow diagrams (MFD).

2.1. Object detection

In recent years, human detection is more attention because of its extensive range of applications in abnormal detection, person recognition, gender classification, and person counting etc. The detection method usually occurs in two steps: object detection and object classification. Object detection method is performed by background subtraction, optical flow and spatial temporal filtering. Background subtraction is a popular method to detect moving objects from the difference between the current frame and a background frame. There are limited approaches to perform background subtraction, which are Gaussian mixture, non-parametric background, temporal differencing, warping background and hierarchical background models. Stauffer C. and Grimson W. (1999) presented an adaptive Gaussian mixture model, which changes dynamic scenes causing from illumination changes. Non-parametric background models study the statistical behaviour of image details to segment the foreground from the background. Kim W. and Kim C. (2012) developed a non-parametric method for background subtraction in dynamic texture scenes. Temporal differencing approach contains three important modules: block alarm module, background modelling module and object extraction module (Cheng *et al*., 2011). Warping background method is a background model that separates between background motion and foreground objects (Ko *et al*., 2010). Chen *et al*. (2012) presented a hierarchical background model to detect and track foreground objects based on region segmentation and pixel descriptors.

Optical flow is a vector-based method which estimates motion by matching points on objects over image frames (Candamo *et al*., 2010; Xiaofei and Honghai, 2010; Efros *et al*., 2003). Optical flow-based methods can be used to detect independently moving objects when the camera is in motion. This algorithm is very complicated and complex computation. Spatial-temporal filtering method uses several adjacent frames to subtract and get different images based on time series image. This method is not applicable for objects not moving and cannot be used for real time applications (Lee, 2005; Ridder *et al*., 1995). In this study, background subtraction technique is used for object detection.

2.2. Object tracking

Object tracking is to track an object (or multiple objects) over a sequence of images. It can be defined as a process of segmenting an object of interest from a video scene and keeping track of its motion, occlusion, orientation etc. in order to extract the useful information (Joshan *et al*., 2012). Broadly object tracking techniques can be classified as point Tracking, Kernel based tracking, and Silhouette Based Tracking**.**

Point tracking method detects objects in successive frames represented by points. The association of the points is based on the earlier object state which can comprise object location and motion. There are three methods to track object based on point tracking, they are Kalman filtering, particle filtering, and Multiple Hypothesis Tracking (MHT). Kalman filter calculate estimations of past, present, and even future states, and it is able to do the same even when the perfect nature of the modelled system is unknown (Joshan *et al*., 2012). The particle filtering generates all the models for one variable before moving to the following variable (Liang and Qin, 2007). This algorithm has an advantage when variables are generated dynamically and there can be limitlessly many variables. Multiple hypothesis tracking (MHT) is an iterative algorithm, Iteration starts with a set of existing track hypotheses (Lee, 2005).

Kernel tracking is typically performed by locating the moving object that is represented by an embryonic object region, from one frame to the subsequent (Joshan *et al*., 2012). There are four methods to track persons based on kernel based tracking, they are simple template tracking, mean shift tracking, support vector machine, and layering based tracking. In template matching, a reference image is verified with the frame that is separated from the video and tracking can be performed for single object within the video and overlapping of object is completed partly. The mean-shift algorithm is to tracking objects whose look is outlined by histograms (Samuel and Blackman, 2004). Support vector machines (SVMs) method is used for classification, regression and outlier's detection (Kim and Sim, 2010). SVM provides a set of positive and negative training values in which the positive values consists of tracked image object, and the negative values consists of all remaining things that are not tracked. Layer based tracking method is to track multiple objects within the crowd. In this method, every layer consists of shape representation, motion like translation and rotation, and layer appearance based on intensity values.

Silhouette-based object tracking is to find the object region in every frame by using an object model generated by the previous frames (Joshan *et al*., 2012). There are two methods to track persons based on Silhouette-based object tracking are contour tracking and shape matching. Contour tracking method is an iteratively progress a primary contour in the preceding frame to its new position in the present frame (Joshan *et al*., 2012). Shape matching is to find matching outlines detected in two consecutive frames.

In this study, crowd tracking is done by TRACKER software (Douglas and Wolfgang, 2011**)**. It is a semi-automatic method and useful when crowd size is very high and helpful when obstructions are present in the study area. While converting pixel to real-world coordinates using calibration stick gives some errors. For this, a direct linear conversion algorithm was applied based on Wolf and Dewitt to minimize the effect of swaying and height difference (Wolf and Dewitt, 2000). The linear algorithm was used for converting pixel coordinates to real-world coordinates.

2.3. Modelling

There are no existing models related to the crowd, but there are models related to pedestrians and most of the models are suggesting that speed-density relationship is linear. Drew D.R. (1968), Fruin J.J. (1971), (May and Harmut, 1967) developed a speed-density relationship as a fundamental relationship, and further, they calibrated speed- flow, flow- density, speed- flow, and flow space using traffic stream (Eq. 1).

$$Q = k \times U, \tag{1}$$

whereas Q - flow, K - density and U - speed.

2.4. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is defined by Dr. Robert Hecht-Nielsen as ''A computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs''. This system is capable of machine learning as well as pattern recognition to their adaptive nature. Florio L. and Mussone L. (1996) evaluated the flow–density relationship of a motorway section to define the time and spacing stability or instability of its motorized traffic flow. For pedestrian detection Zhao and Thorpe used stereo-based segmentation and neural network-based recognition. Dougherty M.S. *et al*. (1993), Smith B.L and Demetsky M.J. (1994) focussed on traffic flow prediction based on ANN approach. Kumar K. *et al*. (2013) developed short-term prediction of traffic volume using past traffic data on NH-58 by using ANN. Sahani R. and Bhuyan P.K. (2014) define LOS levels using ANN clustering. In this study, ANN approach is used for the development of relationship between crowd flow parameters.

The next section explains the study area and the data collection process.

3. Study area and data collection

Study location which is located at Vijayawada, Andhra Pradesh, India is considered for the study. For every twelve years, there will be religious gatherings at all the main rivers in India. Approximately 3.5 crore people take a holy dip during Krishna Pushkaralu. As irregular movements of the individuals, mob formations are more in these type of events. Video graphic data had been collected for a period of 3 hours on August 2016 under normal weather condition. Figure 1 shows the crowded area during Krishna Pushkarams near Padmavathi Ghat.

Figure 1. Crowded study area during Krishna Pushkarams

4. Data extraction

The data was extracted for a period of 3 hours to analyse the crowd behaviour at a macroscopic level. Crowd density is estimated by fore ground detection using background subtraction technique in MATLAB. Also, crowd speed in pixels is extracted using TRACKER software. Conversion of pixel coordinates to real coordinates was done using Wolf and Dewitt (2000). Crowd flow was estimated using fundamental traffic flow (Eq. 1).

4.1. Density Estimation

In this study, background subtraction method is used to assess the crowd density. The number of people in a frame can be counted using foreground detection by background subtraction. The first step is separating the foreground objects from the background reference frames. In the second phase, once the foreground and background are separated, then it will automatically recognize the blobs. The number of blobs represents the number of people in that frame. The ratio of the number of people to the area gives the crowd density.

4.2. Speed Extraction

For the speed extraction, tracker software is used (12). For the extraction of speed, the video is imported into the tracker software, where the tracker automatically converts video into frames. After converting into frames, the coordinate axis needs to be fixed and the point mass is to be created. The speed of the person will be displayed automatically for a selected person. There was no shaking observed while speed extraction because the camera was fixed to a tripod. The pixel coordinates obtained from the video cannot represent person movements in real-world situations because of the camera angle was not perpendicular to the ground. Hence conversion of pixel coordinates to real-world coordinates was required for getting the real world trajectories of individuals. A direct linear conversion algorithm was applied based on Wolf P.R. and Dewitt B.A. (2000) to minimize the effect of swaying and height difference. The lower left corner of the video image selected as the coordinate origin, the relevant conversion formulas are as follows Eqs. (2) and (3):

$$p + \frac{L_1 x + L_2 y + L_3}{L_7 x + L y + 1} = 0, \tag{2}$$

$$q + \frac{L_4 x + L_5 y + L_6}{L_7 x + L_8 y + 1} = 0, \tag{3}$$

where (p, q) is the pixel coordinate, (x, y) is the real world coordinate and L_1–L_8 are transformation coefficients. Eight real world reference points are selected and measured in the experiment sites along with the corresponding pixel coordinates. Four point pairs are used to compute the conversion coefficients and the remaining four are used to check the errors.

5. Modelling the relation between Crowd flow parameters using deterministic models

The relationship between crowd flow parameters were modelled by using the evaluation of macroscopic flow parameters. First model development to observe fundamental relationships between principle flow parameters. In the next, flow parameters such as free flow speed (U_f), optimum speed (U_0), jam density (k_j), optimum density (k_0), and capacity (q_m) were estimated from the fundamental relationships (Eq. 1). Free flow speed is defined as the speed at which density and flow are zero, and jam density occurs in no flow condition. Maximum capacity is defined as the maximum rate of flow or a maximum number of people to cross a point during a given period. Density at maximum capacity is defined as optimum density and speed at maximum capacity is defined as optimum speed. Optimum speed and optimum density can be estimated from the macroscopic flow diagrams (MFD).

5.1. Deterministic modelling

A mathematical model in which outcomes are accurately determined through known relationships, without any room for random variation is called deterministic model. Deterministic speed–density fitted models have been used to observe features of data. Free flow speed, jam density, and capacity were determined using developed models presented in Eqs. 4 and 5.

- Greenshileds model:

$$U= U_f -(U_f /k_j)k \tag{4}$$

- Underwood model:

$$U= U_f e^{- k/k_0} \tag{5}$$

Calibrated models for speed–density relationship with the estimated flow parameters are given in Table 1. From Table 1, it was observed that free flow speed and maximum flow is high for underwood model to Greenshileds model. It was observed that, underwood model is better compared to Greenshileds model. Estimated speed-density, flow–density and flow–speed relationships are given in Table 2. Figure 2 show three flow relationships using deterministic approach.

Table 1. Calibrated deterministic models

Model	Calibration	R value	Flow parameters				
			U_f	U_0	K_j	K_0	Q_m
Model 1 (G)	U=1.323-0.256k	0.895	1.323	0.661	5.16	2.58	102.4
Model 2 (U)	$1.405e^{-0.270k}$	0.913	1.405	0.516	∞	3.7	114.6

Table 2. Relationships between crowd flow parameters using deterministic models

Model	Flow relationships	Calibration
Model 1	Speed vs density	U=1.323-0.256k
	Flow vs density	$Q=1.323k-0.256k^2$
	Flow vs speed	Q=(1.323-u)u/0.256
Model 2	Speed vs density	$U= 1.405e^{-0.270k}$
	Flow vs density	$Q=1.405ke^{-0.270k}$
	Flow vs speed	Q=(u/0.270)(ln(1.405/u))

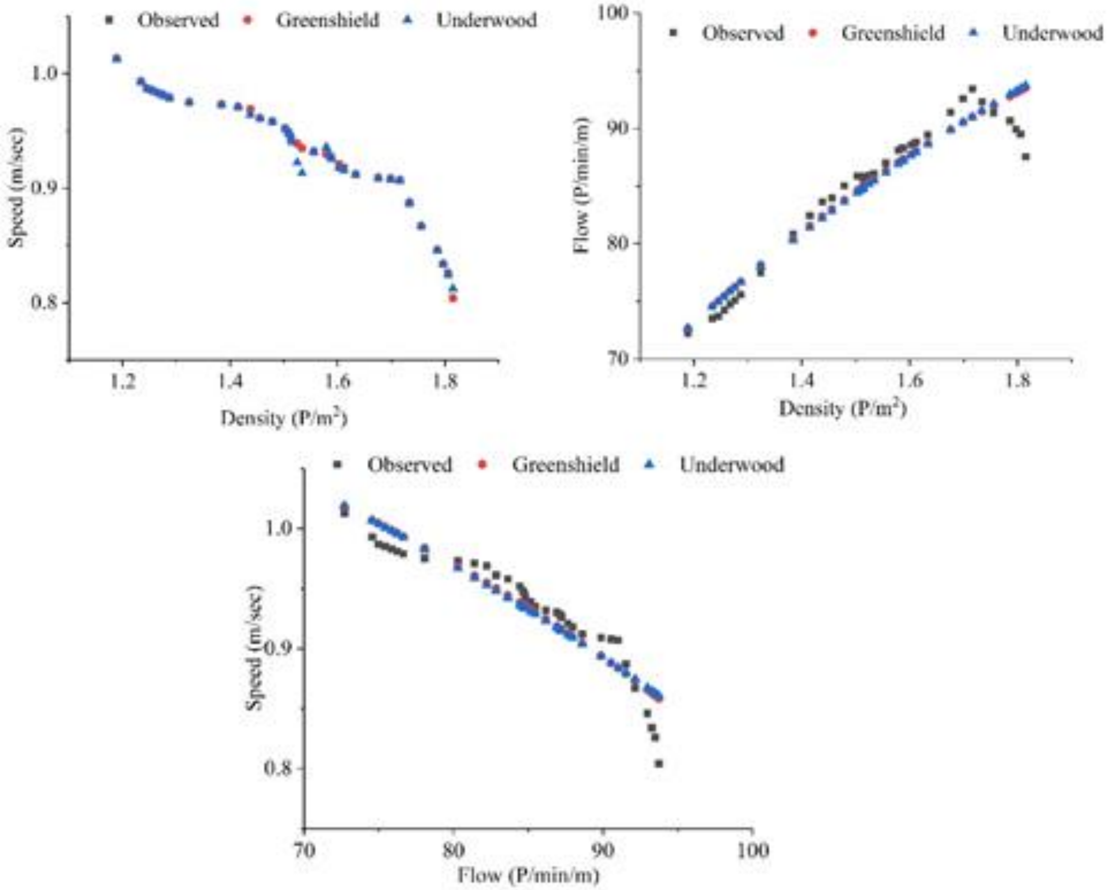

Figure 2. Crowd flow models: Speed–density model, Flow–density model, Speed–flow model

5.2. ANN approach

In this study, ANN approach is adopted to develop crowd flow relationships to introduce nonlinearity phenomena. Deterministic models are made of passive data structures. An active procedure normally manipulates these data structures. Neural network models show global system behaviour observed from local interactions. Learning process of ANN model follows an input-output mapping and adapts their synaptic weights. Four ANN models were developed using NN tool in MATLAB, and the details are given in Table 3. A neural network model consists of processing elements (neurons) and connections (links). The models based on neural network approach is efficient and practical as they facilitate their own implementation and learning based on real data. A network is referred as a layered network where hidden units lie between input and output units. Architectural view of a typical neural network is shown in Figure 3. The neuron inputs are summarized by multiplying the weight factors on synaptic equations, and the output is computed by using neuron activation function in mathematical expression of artificial neural networks. Each neuron also has an input between [-1 1] which is called bias.

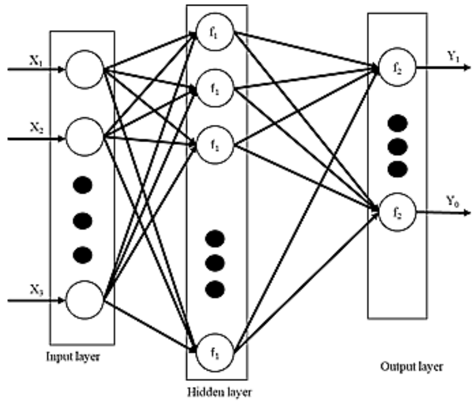

Figure 3. One layer neural networks used for training (sample)

The input nodes provide information from the outside world to the network and are together referred to as the input layer. The input nodes not performed any computation and they just pass the information to the hidden layers. The hidden nodes as a group was called hidden layer and there is no direct connection with the outside world. Hidden nodes perform computations, and transfer information from the input to the output nodes. The Output nodes are collectively referred to as the output layer. Output nodes are responsible for computations and transferring information from the network to the outside world. A two-layer feedforward network trained with Levenberg–Marquardt algorithm is used. Feedforward networks consist of a sequence of layers, and each following layer has a connection with the previous layer, and final layer produces the network's output. For analysis of ANN models, 85 % data for training and 15 % for validation were used. The sigmoid function was used for hidden neuron activation. Mainly, feedforward computation consists of simple run, product, and sigmoid evaluation. Levenberg–Marquardt backpropagation algorithm was used as a network training function which is the fastest backpropagation algorithm. Training may be defined as the first stage of the modelling in the ANN. It can be classified in two groups as supervised and unsupervised. In supervised training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The other type of training is called unsupervised training. In unsupervised training, the network is provided with inputs but not with desired outputs. The system itself must then decide what features it will use to group the input data. This is often referred to as self-organization or adaption. In the neural networks, one forward and one backward pass of all training samples is called epoch. Batch size is defined as the number of samples that are going to be propagated through the network. In this study, total samples were divided into 10 batches (batch size = 50). The number of iterations obtained to cover all the training samples is 10. The number of epochs obtained while training the data was 10. Network performance was measured according to the mean of squared error (MSE). In the used network, sigmoid transfer function was used in the hidden layer and a linear transfer function in the output layer. Performance of ANN models based on crowd flow relationships tabulated in Table 3.

Table 3. Performance of ANN models based on crowd flow relationships

Flow relationships	**Models**	**No of Neurons**	**R**	**MSE**
Speed - Density	ANN 1	5	0.987	1.04×10^{-6}
	ANN 2	10	0.999	1.16×10^{-6}
	ANN 3	15	0.989	1.62×10^{-5}
	ANN 4	20	0.990	2.65×10^{-6}
Density - Flow	ANN 1	5	0.988	0.0537
	ANN 2	10	0.999	2.12×10^{-5}
	ANN 3	15	0.990	0.000134
	ANN 4	20	0.989	7.08×10^{-4}
Flow - Speed	ANN 1	5	0.856	0.000153
	ANN 2	10	0.948	1.44×10^{-6}
	ANN 3	15	0.941	2.95×10^{-6}
	ANN 4	20	0.902	7.02×10^{-5}

It can be observed from Table 3 that ANN 2 model gives better performance as compared to the other three ANN models in terms of R value and performance measure. R measures the relationship between dependent and independent variables. Graphical representation of fundamental crowd flow models using ANN 2 model is shown in Figure 4. From Table 3 Optimum density is 2.41 P/m^2, optimum speed is 0.671 m/s and capacity is 73.64 P/min/m, which are determined using best fitted ANN 2.

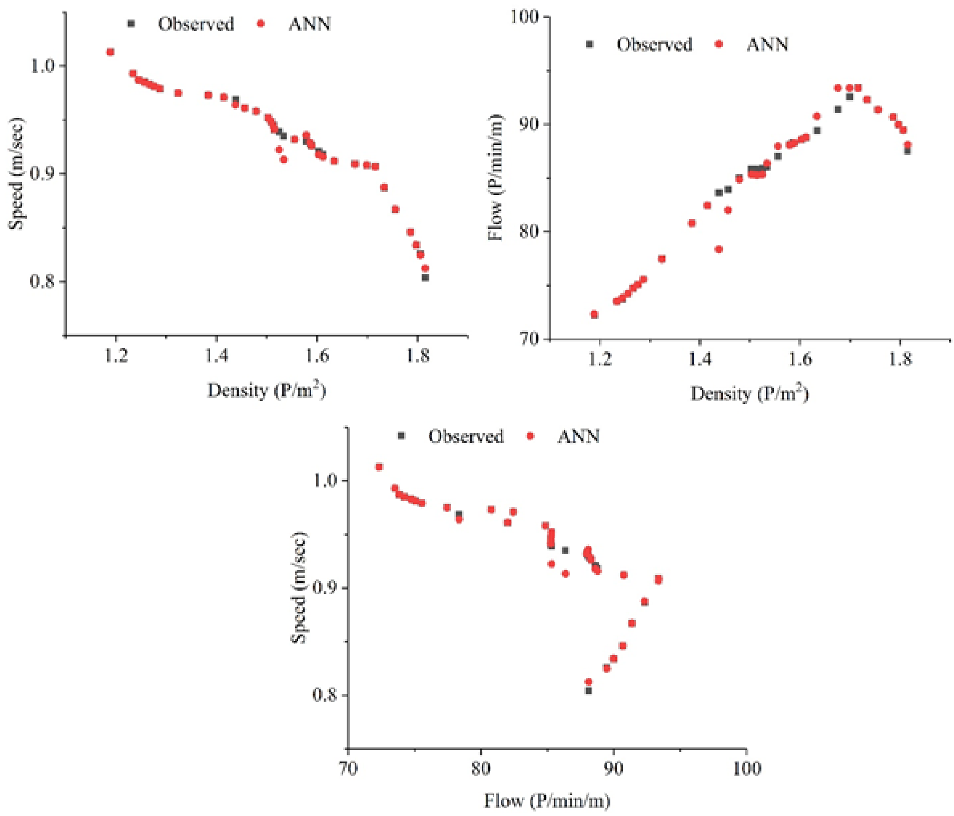

Figure 4. Crowd fundamental flow relationships using ANN.
Speed–density model, Flow–density model, Speed–flow model

5.3. Validation of models

Validation is an essential part of modelling which shows that the model is a realistic representation of the actual system. RMSE and MAE are used for analysing model validation. MAE is useful measure for model evaluation (Eq. 6). RMSE denotes the sample standard deviation which is calculated by the differences between predicted values and observed values. These values are estimated by using (Eq. 7). The RMSE and MAE values for the developed models are given in Table 4. The model which is having less MAE and RMSE value is considered to be the best prediction.

$$\text{MAE (\%)} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - E_i}{O_i}\right|, \tag{6}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(E_i - O_i)^2}{N}}. \tag{7}$$

From the Table 4, by considering RMSE and MAE values, Model II gives better fitness. It can be concluded that, Model II gives better fitness between two deterministic models. Expected and observed speed and flow are plotted in Figure 5.

Table 4. Measurements for model performance and evaluation

Model	Crowd flow relationships	MAE	RMSE
Model 1	Speed - Density	0.0149	0.0189
	Flow - Density	1.4365	1.9357
	Flow - Speed	3.1681	3.8269
Model 2	Speed - Density	0.0148	0.0177
	Flow - Density	1.4017	1.7818
	Flow - Speed	3.2819	3.8921
ANN 1	Speed - Density	0.0024	0.0032
	Flow - Density	0.4467	0.5601
	Flow - Speed	0.5336	0.9863
ANN 2	Speed - Density	0.0014	0.0024
	Flow - Density	0.1936	0.2782
	Flow - Speed	0.4634	0.6443
ANN 3	Speed - Density	0.0017	0.0039
	Flow - Density	4.1879	5.3256
	Flow - Speed	0.5803	1.4030
ANN 4	Speed - Density	0.0015	0.0024
	Flow - Density	0.8681	1.6151
	Flow - Speed	0.4900	0.9213

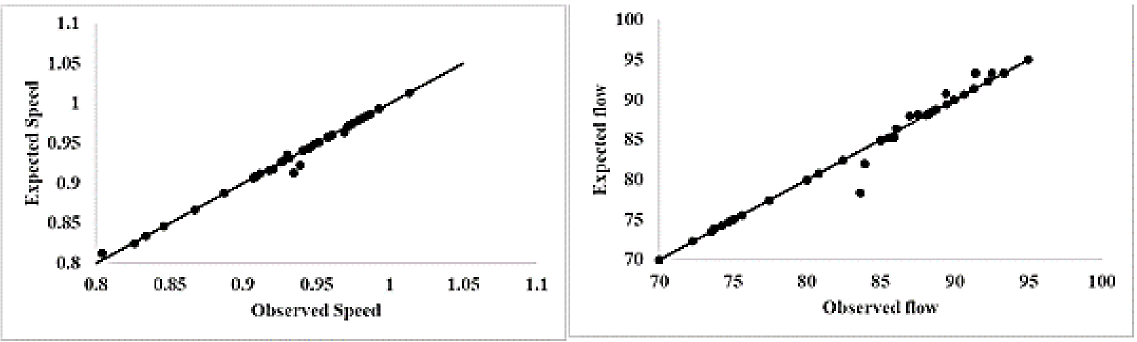

Figure 5. Observed and predicted speed and flow (ANN model): Observed and estimated speed, Observed and estimated flow

The comparison of ANN models, ANN 2 model gives better performance considering overall R, MSE, RMSE and MAE. Estimated RMSE value for ANN 2 model is 3.83 P/min/m considering speed–density, and MAE value is 4.73 m/min. Optimum density is 2.41 P/m^2, optimum speed is 0.671 m/s and capacity is 73.64 P/min/m, which are determined using best fitted ANN 2 model. As per best fitted conventional approach, i.e., Underwood model, Optimum speed is 0.516 m/s, and capacity is 114.66 P/min/m for crowd movement.

6. Conclusions

The relationship between crowd flow parameters explained using macroscopic flow diagrams. Crowd flow models are developed based on two approaches such as deterministic and artificial neural network. ANN approach gives more suitable and realistic nature of relationships of crowd flow parameters (speed-density, flow-density, and speed-flow). The measure of accuracy in terms of performance and validation of models using statistical analysis. Statistical analysis includes correlation coefficient (R), RMSE, MAE. The relationship between observed and predicted values of flow parameters to observe the better performance of the model. It was found that from deterministic approach maximum value of R is 0.913 for Underwood model and 0.999 for ANN 2 (ANN model have 10 neurons) model. The best model is selected based on RMSE and MAE values which can describe crowd flow characteristics in an actual way. ANN model containing10 neurons provide better fitness on comparing it with other models. It can analyse the relationships between flow parameters in an actual scenario considering these statistical measures. ANN gives the best performance rather than conventional approach considering statistical measures.

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