Lane Change Modelling with Fuzzy Logic in Microscopic Traffic Simulation

Madhu ERRAMPALLI*, Masashi OKUSHIMA** and Takamasa AKIYAMA**
*Graduate School of Engineering, **Department of Civil Engineering
Gifu University, 1-1, Yanagido, GIFU 501-1193, Japan,
e-mail: k3812105@guedu.cc.gifu-u.ac.jp

Abstract - In microscopic traffic simulation, lane change phenomenon is considered as vital in representing individual vehicle behaviour. Many lane change models have not considered the uncertainties and perceptions involved while modelling, which are very important to represent human behaviour. In the present study, these uncertainties and perceptions have been considered to represent lane changing behaviour more realistically. For this purpose, a suitable technique namely fuzzy reasoning has been considered. The comparison with observed data indicated that fuzzy reasoning has produced more realistic driver behaviour compared to standard modelling in lane change. The effectiveness of this technique has also been demonstrated by considering a real urban network.

I. INTRODUCTION

Traffic congestion is regarded as one of the major problems in the urban areas and environmental pollution and accidents are deduced out of that. The transport policies such as Travel Demand Management (TDM) especially encouraging public transport system are most appropriate to manage such situation [1]. Before implementing any transport policy, it is prudent to assess their expected impacts. In this direction, microscopic simulation analysis has received higher attention in the last two decades, because they try to analyze realistically each and every individual vehicle/driver behavior in a given time interval more precisely compared to any other method [2]. Though it is considered as most suitable for this purpose, its accuracy and validity mainly depends on the quality of the underlying models of driver behaviour in it.

Basic in any microscopic simulation, the traffic models namely car-following and lane changing models are considered to be the core part to estimate vehicular movements. Car-following model is to estimate acceleration or decelerating, thus position of vehicle on a link. Where as lane change model estimates the decision whether to change a lane or not, based on the goals of an individual driver on multi-lane road [2]. Many a times, vehicle has to change its lane e.g. to take right turn at next intersection, to increase its speed if it has slow leader vehicle, to give way to fast following vehicle etc. And also, vehicle has to change lane in case of transport policy such as restricting lane etc. In such situations, the accurate vehicular movements can not be represented if the lane change model has not been considered in microscopic simulation. Hence, lane change model has equal importance as of car-following model in microscopic simulation.

Lane change model mainly estimates the decision of driver thus the human element and approximations are usually involved [3]. Many lane change models have not described these approximations and human decisions involved in it fully at all the situations. This paper mainly aims on the development of lane change model for microscopic simulation considering uncertainties of driver perception while making the decisions. In that process, an attempt has been made to consider fuzzy reasoning approach to model lane changing behaviour on the urban road network. The developed model has been validated by comparing the estimated lane change behaviour with the observed data. To illustrate the effectiveness of fuzzy logic in lane change model, the results have been estimated using simulation model by considering Gifu city network.

II. LANE CHANGE IN SIMULATION MODEL

A. Lane Changing Phenomenon

Lane change process is mainly applied when a driver seeks to change lane while traveling on multi-lane road. This is initiated if the driver has some purpose and objectives such as take turn at next intersection if the current lane doesn’t allow the intended turn, increase its speed and traffic management measures such as bus lane policy etc. Under this, driver would be continuously thinking whether it is necessary to change lane and is it feasible to change lane as shown in Figure 1.

![Figure 1: Driver Behaviour in Lane Change](image)

While modelling the lane change behaviour, the decision taking process is generally formulated considering these two aspects. The necessity level is generally decided based on the remaining distance/time to reach target turn. If the purpose is to take right turn at next intersection, the location of target turn is the intersection. Necessity is normally classified into three types. They are: unnecessary, desirable and must. Every link is divided into these zones based on the purpose of lane

1Driver and vehicle are considered as one unit in this study
change. The feasibility would be checked based on the gap available in the target lane. If the vehicle is in unnecessary zone, it will not try to seek for a lane change. If it is in desirable zone, it will change lane when ever it finds sufficient gap in target lane [4]. These processes are described schematically in Figure 1. Usually it assumes that driver estimate these two values accurately. But in reality, there are many uncertainties, approximations and perceptions involved.

B. Review of Lane Change Models

In 80’s, Gipps proposed a framework for the structure of lane changing decisions in urban driving situations. However, the model assumes that a lane changing maneuver takes place only when it is safe, i.e. when a gap of sufficient size is available in the target lane [5]. In the last decade, a number of simulation models were developed which incorporated some form of lane changing model [2], [6]. Most publications mention that the implemented lane changing model is based on a set of rules, but the description of the rules is usually superficial and incomplete. Moreover, these lane change formulations are generally not considered any congested environment and always assume that a lane changing maneuver takes place only when it is safe.

Hidas found that this assumption in all lane change models has a serious limitation to deal congested and incident affected conditions [4]. Although some models such as MITSIM in late 90’s stated that they can also model incidents [6], however no information is given on how the model deals with lane changing under such situations. Subsequently, Hidas proposed courtesy lane change (forcible and co-operative) especially to apply for congested and incident situations for SITRAS, a microscopic simulation model [4] and schematic representation of courtesy lane change processes has been shown in Figure 2.

Figure 2: Courtesy Lane Change Process

If gap available is not feasible (congested conditions) to change a lane though the necessity level is must, courtesy lane change would be applied. In this model, courtesy giver vehicle would be identified in target lane in such a way that if that vehicle had forcibly decelerated, sufficient gap can be created to carry out the lane change process by subject vehicle [4]. The congested situations are usually observed on urban roads especially in peak hours and courtesy lane change is essential to describe the lane change behaviour in that situations. The realistic behaviour can not be represented if it has not considered in lane change model.

Subsequently, Wu et al perceived that there are some uncertainties involved in the lane change process which are ignored in Hidas formulations. They also found that mechanistic approaches do not usually incorporate the uncertainties of driver perception and decisions [3]. They proposed FLOWSIM by incorporating fuzzy logic, a technique which allows quantifiable degree of uncertainty into the modelling process in order to reflect ‘natural’ or subjective perception of real variables. But again, this is limited to few purposes and can not handle congested and incident conditions to implement forcible and co-operative lane change (courtesy lane change).

C. Outline of Microscopic Simulation Model

A microscopic simulation model has already been established by the authors by considering various traffic models [7], [8]. In that simulation model, there are mainly two parts namely vehicle generation and movement. The generation part of simulation where vehicles would be generated on the link/network from time-dependent OD (origin-destination) data and route is assigned by route choice model. In movement phase, vehicular movements would be estimated using car-following and lane change model with standard modelling. These operations would be carried out for all the vehicles and sections in each time interval. The detailed description of these can be found in the previous publications of authors [7], [8]. However, a brief description about the lane change model applied in the simulation model and its implications has been given in the following section.

D. Lane Change with Standard Modelling

By making a thorough review of available literature, authors have formulated a lane change model with standard modelling and incorporated in their microscopic simulation model in order to overcome the limitations identified in the previous models.

Though lane changing with standard modeling is able to predict the results with adequate accuracy, some times high lane change rate (events/km/hr) was observed. Moreover, an unrealistic behaviour has been observed. If a vehicle ‘v’ changed lane to improve its speed by considering that its leader is moving slowly, the following vehicle of that vehicle ‘v’ also changes lane by thinking the same. This process continues till the gap is filled in other lane. This situation is not common and rarely observed in the field. Where as in reality, drivers consider distance to leader vehicle as well. If one vehicle change lane, the preceded vehicle will not change lane immediately as it got some distance to increase its speed unless it is mandatory. Further, this model has not considered lane changing for other purposes such as vehicle parked on roadside, bus stop etc. To make the model more realistic, there is a need to consider other appropriate explanation variables and also other approaches which consider human perceptions. After reviewing available techniques, it has been considered that fuzzy logic is most appropriate for such kind of situations.

III. LANE CHANGE MODEL WITH FUZZY LOGIC

A. Necessity for Fuzzy Logic

Lane change process is carried out to estimate the decision of lane change by considering many input parameters such as speed, position of leader and follower vehicle in the same and target lane, gap in target lane, and distance remaining to target turn. Fuzzy reasoning would be considered as appropriate technique because of the following reasons:

- All the above mentioned input parameters are not crisp
values and can not be estimated exactly by a driver. In reality, there is fuzziness involved in all of them.

- Every decision of driver (i.e. intention of driver to change lane or not) has fuzziness and moreover human approximations are involved in it.
- There are no adequate mathematical relationships established between these. Thus the inference system possesses high non-linearity.
- Rule base (IF...THEN... rules) with fuzzy reasoning has close resemblance of human knowledge and behaviour as they use linguistic terms and they are capable of handling complicated situations using certain rules.
- To handle such situations, the standard rule base would become so large and not applicable for some situations. In case of addition of any new input variable, this rule base becomes more complicate. On contrast, rule base with fuzzy reasoning simplifies the rules by making the variables into groups using linguistic terms.

By reviewing these factors, a lane change model has been proposed to consider fuzzy reasoning in this study.

B. Fuzzy Reasoning Approach

Fuzzy reasoning is an application of fuzzy set theory to ordinary reasoning. The fuzzy reasoning process is summarized with three elements namely implication from inference rules, integration of conclusions and defuzzification [9]. The popular implications are min-operation and product-operation. In case of min-operation, the fuzzy set in inference result is clipped off corresponding to the value of truth to the condition of the rule, whereas it is scaled in product-operation. The inference results are integrated into a single fuzzy set from different inference rules. The primitive approach is max-operation. It can be interpreted that the max-operation corresponds to the union (also sum) of fuzzy subsets. For defuzzification, center of gravity of the distributed area is often considered as a representation in conclusion [9]. Since min-max-gravity method generates undesirable non-linearity [10], product-sum-gravity has been proposed to many applications in the practical fields. It had also been reported that linear inference methods like “product-sum-gravity” might provide better performance [9], [10] and easy to tune besides its simplicity and low computations. The product-sum-gravity method is summarized as follows:

Let, (x, y) are linguistic variables on the input space X × Y and z is a linguistic (or real) variable on the output space Z, then the fuzzy inference rules can be generally expressed by following equation:

\[
IF \ x \ is \ A_i \ AND \ y \ is \ B_i \ THEN \ z \ is \ C_i
\]

where \( A_i, B_i \) and \( C_i \) are fuzzy sets on universe \( X, Y \) and \( Z \) respectively and \( i = 1, 2, \ldots, n \) is the \( i^{th} \) fuzzy inference rule.

When a set of input data \((x_0, y_0)\) is given, the antecedent part in the \( i^{th} \) rule becomes the following equation to estimate implication result using algebraic product of membership values:

\[
\mu_{C_i}(z) = \mu_{A_i}(x_0) \times \mu_{B_i}(y_0) \times \mu_{C_i}(z)
\]

Therefore, the composition of all rules is calculated by summing the implication results algebraically as shown below:

\[
\mu_C(z) = \sum_{i=1}^{n} \mu_{C_i}(z)
\]

As a whole, min-operation is replaced by product-operation and sum is introduced instead of max-operation to summarize the parallel conclusions from all rules.

The min-operation would be clipping off the fuzzy set and the implication result becomes flat and same for some values of lane change decision. But, the intention of lane change decision corresponding to the truth from antecedent condition can not be constant and vary across different values. The product-operation considers this effect and the implication result would be scaled across the values of lane change decision so that every decision has different weightage from each other. In lane change behaviour, drivers respond to small change in the variables and need to consider the influence of all inference rules in the conclusion. The sum operator is able to consider the implication results simultaneously by summing and take all the implications into conclusion so that even small implication is considered in lane changing decision. Therefore, the “product-sum-gravity” operation is considered as appropriate and implemented in fuzzy reasoning to produce the practical lane change model.

IV. PROPOSED LANE CHANGE MODEL

A. Outline of Proposed Model

In the standard modelling, lane change process mainly carried out by estimating necessity level and feasibility for each purpose. Based on these, lane change decision is determined. In case of fuzzy reasoning, intention of lane change is determined from product-sum-gravity method using fuzzy inference rule base as shown in the form of flow chart in Figure 4.

Figure 3: Process involved in Lane Change Model

If decision is ‘change lane’ and there was no feasibility, then courtesy lane change module would be applied. Fuzzy rule base describes driver’s intention for a lane change based on their input variables. A lower intention indicates a lower possibility for a lane change and vice versa [3].

B. Influencing Variables and Inference Rules

In the present study, it is proposed to consider four types of lane changing purposes. They are: (i) Speed advantage, (ii) Turn at next intersection, (iii) Priority bus lane policy and (iv) Presence of bus at bus stop or Parked vehicles along roadside. The input variables considered are Speed Advantage (SPA), Feasibility Level (FSL), Remaining Distance to Target Turn (RDT), Distance to Leader Vehicle (LVD) and Distance to Follower Vehicle (FVD). The output variable considered is the Intention of Lane Change (LCN). The variable SPA (in
functions have been assumed for each of input and output activity, only three fuzzy sets with triangular membership (consists of 54 rules) has been formulated to determine the functions of all variables, appropriate fuzzy rule base and High. The typical fuzzy sets for input/output variable and measured in meters. As lane changing is more sophisticated intention of lane change [3]. Hence the rules have been purpose considers certain input variables which influence the purpose and it is clearly different from each other. Each purpose has been schematically represented in Figure 6. 

For each input/output variable, the parameters a, b and c have been appropriately and logically assumed to determine the shape of memberships functions. The assumed parameters of each input and output variable membership function have been depicted in Figure 4. After creating the membership functions of all variables, appropriate fuzzy rule base (consists of 54 rules) has been formulated to determine the decision for each purpose differently and the same has been presented in Figure 5.

For each purpose the following rules have been formulated separately and detailed descriptions have been given in the following sections for each purpose.

C. **Speed Advantage Purpose**

When driver encounters a slow leader, he seeks to increase his speed by changing lane. For this process, three influencing variables have been considered. They are: SPA, LVD and FSL. Then, driver checks these three variables and apply appropriate rules from rule base to determine his level of intension of lane change. The lane change under this purpose has been schematically represented in Figure 6.

As described in the figure, if SPA is high, FSL is high and LVD is high, then LCN is Low. The variable LVD plays important role here. Because LVD is high, driver has some space to increase his speed by staying in the current lane itself. Hence the intention of lane change is low even though SPA and FSL are high.

D. **Turn at Intersection Purpose**

Under this purpose, the driver look for a lane change to fulfill his goal such as take left or right turn at next intersection when the current lane doesn’t allow the intended turn. For this process, RDT and FSL have been considered as influencing variables. Then, driver checks these two variables and apply appropriate rules from rule base to determine his level of intension of lane change. The lane change under this purpose has been schematically represented in Figure 7.

As shown in the above figure, if RDT is high and FSL is high, then LCN is low as shown in above figure. Because RDT is high here and driver has got some space and time to reach target turn, then the intention of lane change is low.

E. **Priority Bus Lane Policy Purpose**

Usually no vehicle is permitted to use bus lane, but in this policy, private vehicles are also permitted to use bus lane provided that they give no hindrance and give priority to traveling buses in bus lane. Private vehicle which is traveling on bus lane keep on checking the gap between its’ own vehicle and its’ follower vehicle and it changes to ordinary lane if the follower vehicle is bus and it is closer to it. For this process, FVD and FSL have been considered as influencing

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![Figure 4: Fuzzy sets and linguistic description of variables](image)

For each input/output variable, the parameters a, b and c have been appropriately and logically assumed to determine the shape of memberships functions. The assumed parameters of each input and output variable membership function have been depicted in Figure 4. After creating the membership functions of all variables, appropriate fuzzy rule base (consists of 54 rules) has been formulated to determine the decision for each purpose differently and the same has been presented in Figure 5.

**Figure 5: Inference rules for lane changing model**

The motivation for lane changing varies based on the purpose and it is clearly different from each other. Each purpose considers certain input variables which influence the intention of lane change [3]. Hence the rules have been formulated separately and detailed descriptions have been given in the following sections for each purpose.

<table>
<thead>
<tr>
<th>(i) Speed Advantage Purpose:</th>
</tr>
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<tbody>
<tr>
<td>R-1 If SPA is Low AND FSL is Low Then LCN is Low</td>
</tr>
<tr>
<td>R-2 If SPA is Low AND FSL is Low AND LVD is Low Then LCN is Low</td>
</tr>
<tr>
<td>R-26 If SPA is High AND FSL is High AND LVD is Medium Then LCN is High</td>
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<tr>
<td>R-27 If SPA is High AND FSL is High AND LVD is Low Then LCN is Low</td>
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<th>(ii) Turn at Intersection Purpose:</th>
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<tbody>
<tr>
<td>R-28 If RDT is Low AND FSL is Low Then LCN is High</td>
</tr>
<tr>
<td>R-29 If RDT is Low AND FSL is Medium Then LCN is Medium</td>
</tr>
<tr>
<td>R-35 If RDT is High AND FSL is Medium Then LCN is Low</td>
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<tr>
<td>R-36 If RDT is High AND FSL is Low Then LCN is Low</td>
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</tbody>
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<th>(iii) Priority Bus Lane Policy Purpose:</th>
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<tbody>
<tr>
<td>R-37 If FVD is Low AND FSL is Low Then LCN is High</td>
</tr>
<tr>
<td>R-38 If FVD is Low AND FSL is Medium Then LCN is High</td>
</tr>
<tr>
<td>R-44 If FVD is High AND FSL is Medium Then LCN is Low</td>
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<tr>
<td>R-45 If FVD is High AND FSL is Low Then LCN is Low</td>
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<tr>
<th>(iv) Bus Stop / Parked Vehicle Purpose:</th>
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<tr>
<td>R-46 If LVD is Low AND FSL is Low Then LCN is High</td>
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<tr>
<td>R-47 If LVD is Low AND FSL is Medium Then LCN is High</td>
</tr>
<tr>
<td>R-53 If LVD is High AND FSL is Medium Then LCN is Low</td>
</tr>
<tr>
<td>R-54 If LVD is High AND FSL is Low Then LCN is Medium</td>
</tr>
</tbody>
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![Figure 6: Lane Change for Speed Advantage Purpose](image)

As described in the figure, if SPA is high, FSL is high and LVD is high, then LCN is Low. The variable LVD plays important role here. Because LVD is high, driver has some space to increase his speed by staying in the current lane itself. Hence the intention of lane change is low even though SPA and FSL are high.

![Figure 7: Lane Change for Turn at Intersection Purpose](image)

As shown in the above figure, if RDT is high and FSL is high, then LCN is low as shown in above figure. Because RDT is high here and driver has got some space and time to reach target turn, then the intention of lane change is low.
variables. Then, driver checks these two variables and apply appropriate rules from rule base to determine his level of intention of lane change. The lane change under this purpose has been schematically represented in Figure 8.

Figure 8: Lane Change for Bus Lane Policy Purpose

As shown in the figure, if FVD is high and FSL is high, then LCN is low. Because FVD is high in this case, driver has some time to change lane. When ever bus approaches closer to it, it would go for a lane change. If FVD is low and FSL is low, then the intention becomes high to give priority to bus.

F. Bus Stop / Parked Vehicle Purpose

The driver seeks to change lane when he finds a bus stopped at bus stop or parked vehicle along roadside. For this, LVD and FSL have been considered as influencing variables. The driver checks these two variables and applies appropriate rules from rule base to determine his level of intention of lane change. This process has been schematically represented in Figure 9.

Figure 9: Lane Change for Bus Stop Purpose

For example, if leader vehicle distance (LVD) is low and feasibility (FSL) is medium, then Intention of Lane Change (LCN) is high as shown in above figure.

G. Advantages of Proposed Model with Fuzzy Logic

The merits of this model with fuzzy logic over previous models and standard modelling have been given below:

- Adverse lane change behaviour (refer section II.D), which was identified in standard modelling has been eliminated, thus leading to realistic behaviour.
- Uncertainties of driver perceptions can be considered
- Many types of purposes would be able to consider
- This lane change model can be applied in congested situations also as it considered courtesy lane change.

V. APPLICATION OF LANE CHANGE MODEL

A. Validating with Observed Data

Before application, the present formulation in lane change model has been validated. It was proposed to collect the real lane change behaviour of driver from the field through video recording and compare with the estimated results from the model. For this purpose, Kinka Bridge Road of Gifu city network has been selected and the location has been shown in Figure 10.

Figure 10: Selected Gifu City Network

Individual lane change behaviour has been carefully studied and comparison of estimated behaviour with fuzzy logic and standard modelling with real observed behaviour has been carried out for different time intervals and the same has been presented in Figure 11. It can be seen from the

Figure 11: Comparison of Observed Driver Behaviour with Lane change model with Fuzzy Logic and Standard Modelling
observed vehicle movement from the figure that subject vehicle has changed lane gradually. In case of estimated vehicle movement with fuzzy logic, vehicle has changed lane almost near the same place of observed, where as in lane change with standard modelling, vehicle had delayed and lane changed at different place as observed. From this, it can be inferred that lane change model with fuzzy logic has been predicting the behaviour which is closer to real compared to standard modelling. The collected data has also been further analysed and estimated lane changing events/km/hr. This data has been compared with estimated value using microscopic simulation model and presented in Figure 12.

![Figure 12: Comparison of Lane Change Rate](image_url)

From this figure, it can be seen that the lane change model with fuzzy logic has been estimating almost closer to observed data, thus represents the accuracy of fuzzy logic.

B. Application of Lane Change Model to Urban Network

The Gifu city network (60 nodes and 204 links) has been selected as shown in Figure 10 to demonstrate the applicability of proposed lane change model with fuzzy logic. The vehicular movements have been estimated using microscopic simulation model and from that hourly link flows (07:00-08:00) have been estimated. These estimated link flows have been compared with observed hourly link flows and calculated RMS error. It has been observed that RMS error was reduced from 301 veh/hr to 253 veh/hr by incorporating fuzzy logic approach in lane change modelling. Further, lane change rate (events/km/hr) has been calculated for all links and comparison of frequency distribution of the lane change rate for lane change model with fuzzy logic and standard modelling has been presented in Figure 13.

![Figure 13: Frequency Distribution of Lane Change Rate](image_url)

From the above figure, it can be observed that lower lane change rate is more for lane change model with fuzzy logic and higher rate is more for standard modelling. Thus, fuzzy logic (mean=310 events/km/hr) is producing lower lane change events compared to standard modelling (mean=404 events/km/hr). From all these, it can be said that lane change model with fuzzy logic is able to estimate the lane change behaviour with sufficient accuracy and closer to real behaviour.

VI. CONCLUDING REMARKS

Decisions and actions of a driver while changing lane are believed to follow a reasoning process based on vague logic. The proposed model applies the inference system and simulates lane changing phenomenon. In this study, lane change model with fuzzy logic has been proposed and formulated for a microscopic simulation model. The purpose of the paper is to present the methodology of building the model. The shapes of specific memberships functions used in the model must still be verified through filed data collection. The summary of findings of the present study is as follows:

- The proposed lane change model with fuzzy reasoning is capable of considering courtesy lane change which is essential in congested situations.
- The proposed model estimating the lane changing behaviour more realistically and overcame the problems faced by standard modelling.
- The developed model estimated lane change behaviour and lane change rate closer to observed data compared to standard modelling.
- Lane change model with fuzzy reasoning has also improved accuracy by reducing RMS error in estimating hourly link flows for the urban network.

Hence, the selection of appropriate technique for modelling purpose is very important as it influence the final result and the decision making in implementing transport policies as well. Therefore, it is concluded from this study that technique such as fuzzy logic is most appropriate especially lane change model for microscopic simulation.

In future scope of this study, it is proposed to consider the fuzzy sets into more groups and calibrate the parameters of memberships functions using advance technique such as Genetic Algorithm (GA). Further, it is also recommended to collect data from the field to calibrate and validate the parameters of membership functions.

REFERENCES