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SPECIAL ISSUE

An improved analytical approach for customer churn prediction using Grey Wolf Optimization approach based on stochastic customer profiling over a retail shopping analysis: CUPGO

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Abstract
Challenge of an early prediction of customer churn is a major demand among research community. To understand an intention of a customer on reasons to make a churn as well time taken by a customer to churn is always an unknown mystery. Though good numbers of research works have suggested works on customer churn an exact measure of accurate churn and approaches to suggest on retention is the major discussion of this paper. Traditional approaches such as ACO, PSO are supports on appreciable churn prediction but consider more time to converge, whereas GWO algorithm supports with minimal time to converge as well improved accuracy of 89.26% along with actual churn match compared to PSO and ACO approaches. CUPGO also focuses on customer retention of 34.81% to retain valuable customers. CUPGO works on a large dataset collected over two consistent years.

Keywords Churn prediction · Grey Wolf Optimization approach · MAPE · Retention rate

1 Introduction

Today's businesses depends on customer as a major asset, hence an ability to improve retaining customer as an asset is a major concern [1, 2]. Hence, the need for a model to retain existing customers to improve the business institute brings in customer acquisition which is a costly affair. Numerous research works discuss on customer identification who have maximum chance of likelihood to churn, as well as support targeted marketing campaigns which do support on bringing on customer to stay. Research works on early identification of potential churners bring in detainment of customer churn, hence relates to the profitability for a retail store or a business institute, which involves in selling of products.

Research and analysis [3, 4] suggests that there is a need for the system to become more proactive towards churn prediction, hence the need for support for more investment of customer retention is the major demand. Researchers insist that the need for developing machine learning-based models with support for data analytics including churn analysis, prediction and management is on demand. Research objective of this work focuses on development of a dynamic model which can forecast the customer behaviors of churn.

An early prediction of customer churn depends on optimized accuracy, efficiency in forecasting, hence need for an optimal swarm intelligence approach is expected from researches view point. This research works on Grey Wolf Optimizer (GWO) [5, 6] which supports on specific churn prediction for customer retention analysis forecasting. CUPGO optimization works on analytic performance of Grey Wolf food foraging behaviour which are compared against results of Ant Colony Optimization (ACO) algorithm, Particle Swarm Optimization (PSO) algorithm [7, 8]. CUPGO approach measures on accuracy and Mean Absolute Percentage Error (MAPE) [9] for percentage of prediction accuracy as a major metric of analysis. The MAPE determines error size (%), whose scale sensitivity can be used for large volume of data. MAPE is observed as an average of the unsigned percentage error analyzed. CUPGO shows

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significant improvement of accuracy results as compared to the PSO, ACO algorithms.

CUPGO involves the process of predicting multiple approaches of customer churn based on distinguishable stochastic patterns from datasets using an anomaly detection or outlier detection. CUPGO research approach follows regression based distance that uses a hybrid model of k-nearest neighbor (kNN) [10] and Grey Wolf Optimization (GWO) [5] to predict on chances of customer churn. Good analysis and measurement of customer satisfaction with customer loyalty supports on Net Promoter Score (NPS) [4] as major analytical understanding in any churn analysis.

The paper is arranged with Sect. 1 focusing on introduction to customer churn, Grey Wolf Optimization, while Sect. 2 discusses on detailed survey and analysis of customer churn in relation to early prediction model over Grey Wolf Optimization and other related approaches. Section 3 focuses on CUPGO model based design approach based on Grey Wolf Optimization with customer churn nearest neighbourhood prediction model which brings in possible optimization to early prediction. Detailed algorithm design and implementation is carried out in Sect. 4 while Sect. 5 focuses on experimental results and analysis and Sect. 6 concludes on outcome of work and future part of research work.

2 Survey and analysis

Customer retention model supports on methods of reducing defection [11] hence supports on reducing customer churn as well as improving customer maintenance as an asset. Customer profiling and churn management are interrelated research phenomenon which goes into analysis for customer retainment [12]. Lot of research works do deliberate on aspects of churn analysis and early prediction but the accuracy in prediction is a major misnomer towards feature extraction and modelling approach.

Verbeke et al. [13] discusses about importance of customer profiling and online customer purchase behaviour. Customer profiling is considered as major outlook of work, while this paper discusses on using Service Oriented Architecture as the implementation model. This approach uses feedback mechanisms adopted to determine customer interest and predict churn. Yang et al. [14] adopted regression tree models using Matlab. The model developed using the chosen technologies such as Linear Regression or Regression Tree model adopt the same training dataset which comprises of 702 customers with a 50:50 ratio defined as churners and non-churners. Frequent survey [15] on customer churn in the aspect of research follows popular knowledge based models such as neural networks as an advanced learning approach. In research, authors Laszczyk et al. [9] investigate on the suitability of adapting multiple technologies for predicting customer churn based on complaints and feed back of customer data collected at continuous period of time.

Ganghishetti [2] analysed customer churning based on neural network models. Zang's model [16] or approach adopts a sample set of data for training the models. The approach uses classification and regression trees which are being constructed based on specific criterion to validate the search criteria and meet the outcome. Mozer [17] work suggests on neural network model which decides its work as customer relationship management (CRM) which deserves n the need for efficient and accurate means of prediction, where as it also determines that a potential risk to predict the sub-optimal solutions, and suggests for over fitting the customer churn prediction curve when compared over a random forest or decision tree.

Research works suggest that learning algorithms such as neural networks show an improved churn prediction than decision trees and logical regression [18]. Various mining and computational techniques are presented to address the issues of churn as risk analysis. Verbeke et al. [13] discusses about churn analysis using localization problem. Filho et al. [19] suggested on a detailed literature survey which is significant to churn risk analysis and probable churn prediction. Sugumaran et al. [20] designed an efficient customer retention system to bring back the churned customers by extending the customer behaviour with accuracy over search criteria towards prediction on churn. This approach uses ACO as a computational approach to predict chances of churn. Accuracy rate towards prediction is limited to small dataset and system achieves local convergence. Rosta et al. [15] proposed a refinement phase over ACO towards improving the churn prediction accuracy by measuring the cluster neighbourhood distances between adjacent churn behaviour observed.

Parapar et al. [6] handled the issue of error accumulation in customer churn with support of Kalman filter based on neighbourhood analysis recommendation based churn estimation approach to consistently monitor churn activities and handle challenges behind error handling. Subramaniam [21] proposed bee hive optimization approach to predict early customer churn. This approach CCHUM depends on activities of bee which determine quality of data based on its activity analysis. Though this approach is better towards time conservation and detection, accuracy towards prediction is not critical.

An analytical research suggested by researchers proposes on GWO algorithm provides better performance in terms of prediction accuracy and minimization of time to converge. This approach supports on fast convergence of cost involved towards search criteria based on customer churn risk factors which help in determination of Key Performance Indicators which can determine worthiness of customer to be tracked. Survey on GWO algorithm [4] predicts optimal performance towards improving the search criteria as it adopts the strategy of hierarchical leadership t depute tasks to sub-ordinate wolves.

2.1 Research motivation

The primary motivation behind this research supports on prediction of early customer churn, where the need for understanding customer risk is major discussion. The proposed work focuses on understanding Average Customer Lifetime in purchasing the product, which suggests on customer quality as valuable customers and non-valuable customer. Proposed model defines Total Customer Value which considers customer feedback and predicting probable exit point to clear the purchase procedure. The approach looks into the minimum computation time along with early prediction and understanding customer quality which are the advantage of GWO.

The research gap suggests the design of an improved GWO approach which considers customer risk as a valuable parameter of churn prediction along with clustering of different customer profiles based on purchasing behaviour, quality of product purchased, time taken for a product purchase, along with Customer Life Value as major parameters involved in purchasing activity. From survey and analysis the challenge also lies in early prediction of churn with optimal time to converge and cost involved towards churn. The improved method of GWO brings in the challenge of improving accuracy and suggestion customer retention rates.

3 Design and model of CUPGO using Grey Wolf Optimization with k-nearest neighbourhood

An analytic of customer churn adopts to various domain of research in field of applied statistics [11, 22], marketing, related aspects of data mining which applied domains of modelling approaches, which attempt to predict churn at any instant of time. This work suggests on a hybrid optimization approach which considers hybrid optimization approaches determine on combination of two or more soft computational or meta-heuristics algorithms which can be merged together to form a new optimization algorithm which support towards efficient analysis to determine the optimal deterministic solution within minimal computation time. Some researchers [23, 24] used the hybrid algorithm to solve the localization problem.

3.1 Understanding customer churn

Customer is always taken as the major asset of any business organization. It is important to maintain and manage the valuable aspects of customer and their products being purchased. Figure 1 shows the customer activity period observed over discrete intervals of time period for the study carried out.

From the Fig. 1 it can be observed that the customer walk in time into a business institute defined to be retail shop which sells products. The study observed the customer behaviour at any instant of time ‘t’, which relates to customer “buying” a product or returning without making a purchase. Following definitions explain the role of customer towards product purchase and the process involved in depicting customer.

(a) Customer commitment [25]: Customer values the business institute with high regard and supports the product value. Customer does not easily change a product or business institute due to the value being carried by institute in market. Hence customer is committed to buying only from that institute or indicates negligence to change. This shows a high customer affection and their assets are major resources of profit.
(b) Customer retention [9, 25]: Depicts the chances of retaining the customer from making a churn due to any change over. The phenomenon of “change over” or churn happens due to an external event supported due to customer behaviour of product purchase.
(c) Customer churn [26]: The phenomenon of a customer churn happens primarily due to a “non-interest” nature of customer to move out of a business institute. Research works interested in prediction of customer renewal and usage behavior of product purchase should be known in advance in order to avoid a churn.
(d) Customer alert and renew [2]: Indicates the chances of retaining the customer and maintain the asset of a business institute. An alert indicates an early prediction approach where a business institute takes precautionary steps to avoid a churn and suggests the customer to renew and continue with same institute.

Purchase of a product by a customer depends upon, interest of customer towards buying the product, product

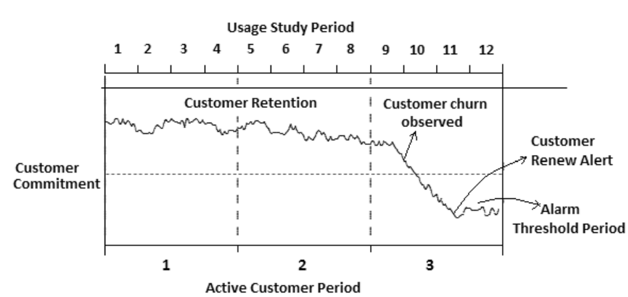

Fig. 1 Customer churn analysis over a study period

utilization factor, and cost as major metrics to analyse. Each customers purchase behaviour characteristics depend upon: (1) number of latest purchases, (2) frequency of purchases (number of past purchases), (3) interested products (4) understanding demand (5) price limitations. The mapping existing between customer and product depicted in Fig. 2 show the mutual relationship elaborated over multivariate objectives [4]. Prediction of a churn at any instant of time indicates a loss to business organization, hence immediate need to look into customer care is a major demand of research.

Relative metrics of customer buying a product and their purchase activity leads to a mapping between customer and product. Purchasing activities of customer being monitored and data gathered over consistent period of time helps in analysis of customer and their interests. The active time taken by customer towards buying the product is from entering into the shopping market and final billing process with instant feedback.

3.2 Grey Wolf Optimization

CUPGO which explains an analytical approach for early prediction of customer churn using Grey Wolf Optimization approach based on stochastic outliers is a simple and novel approach. This approach adopts the knowledge of stochastic customer behaviour as predictable outliers to suggest on churn prediction among detectable customer trained dataset.

Marjalili et al. [24] suggested Grey Wolf Optimization approach, which is inspired by grey wolves prey hunting behavior and works on different aspects of wolves hierarchical leadership hunting strategy. Grey wolves live and hunt together in a group and are considered as top-level predators in a group size of 5–12 wolves. Their hunting strategies [27] adopt categories of alpha, beta, and delta where each group of wolf adopt different hunting approach as a leader, assistant wolves which involve in decision making, subordinate wolves and scouts or scape goat. GWO hunting adopt following steps to achieve the target:

1. To approach the target prey by tracking and chasing
2. To encircle target prey and harass the prey until it is mobility is stopped
3. Attack the prey with all hunters

Grey Wolf optimizer analyzes on customer buying pattern consistently (Fig. 3) as well as prepares to maintain high correlation with product class labels of dataset. Instances of product buying and its pattern/event predicts on customer behaviour and its relationship indicated using the maximum

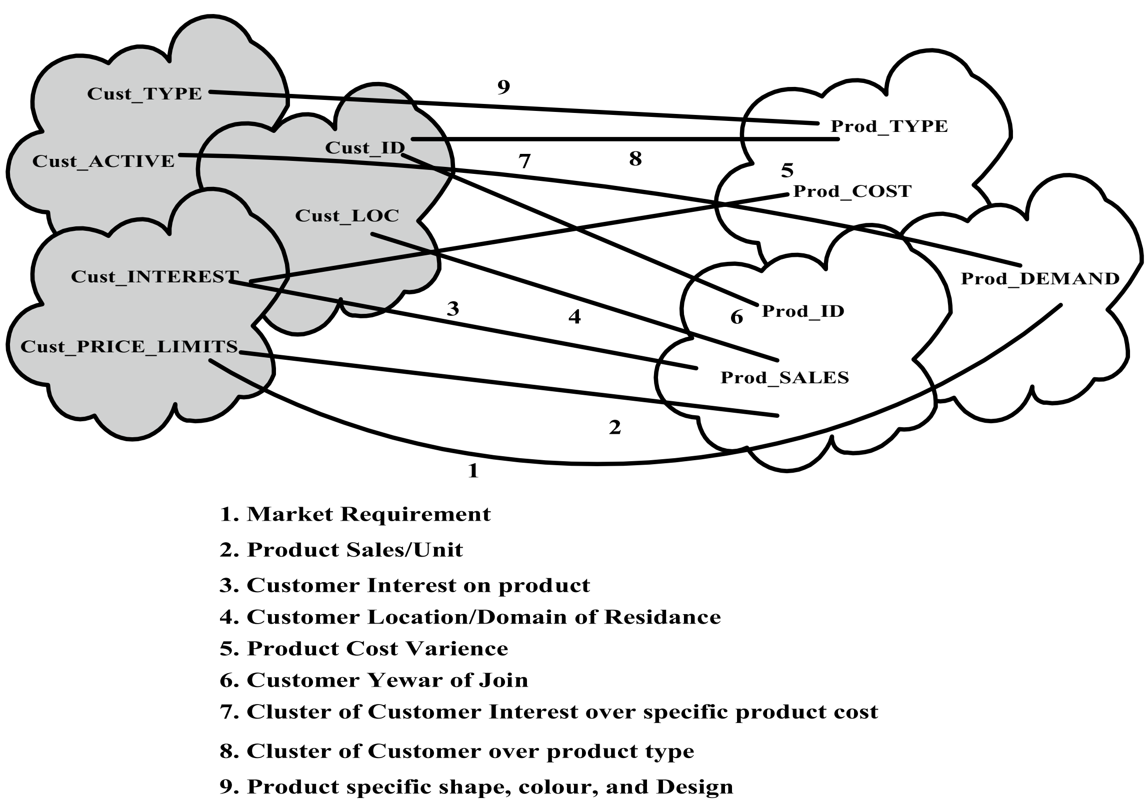

Fig. 2 Customer index and product index mapping

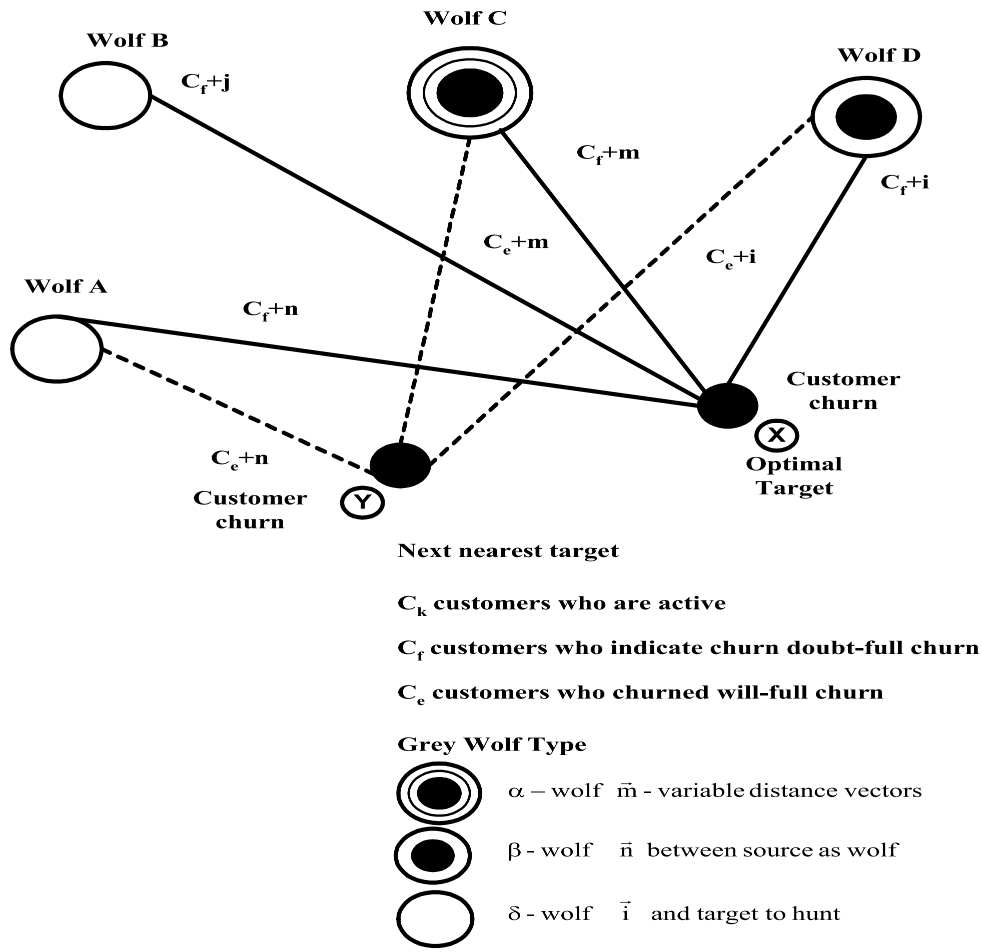

Fig. 3 Customer churn analysis implemented using GWO and distance vector approach

relevance criterion which selects on instances which are near as well as mutually far away from each other, to support on minimum redundancy. As in Fig. 3, 'm', 'n' and 'i' are variable distance vectors.

To understand the notion of customer churn or dropout, Grey Wolf Optimization approach suggests on analysis of customer behaviour over varied time intervals as a major feature to be verified. Each customer as an individual is considered to be active at any specific time implies which suggests that underlying purchasing behavioural trait should be considered to suggest on renewal threshold for renewal periods.

CUPGO model includes three churn processes being followed at individual level [11]:

1. Time taken for a customer being involved for commitment over a product.
2. Time taken by a customer for renewal (rejoin) process which is observed after a churn.
3. Time taken among group of customers who indicate a chance of churn but does not churn based on a business institute or retail store policy.

GWO involves process of selecting the optimal target as prey resembles by encircling and attacking the prey by exploitation phases: (a) explore all possibilities for optimal target solution in search space, (b) recognize the location of target prey and encircle them. The role of encircling the prey involves position vector of X and Y. Equation (1) is represented as:

$$\begin{aligned}\vec{A} &= \left|\vec{Y}\cdot\vec{Xp}(k) - \vec{X}(k)\right| \\ \vec{A}(k+1) &= \vec{Xp}(k) - \vec{X}\cdot\vec{Y}\end{aligned} \tag{1}$$

where 'k'—current iteration of target prediction, X and Y—coefficient distance vectors between the targets and search wolf, Xp—position vectors of target churn, A—search wolf involved, (k + 1)—next optimal search of target new position vector computed by an average sum of all target wolf positions.

To predict on location of next target, the wolves change their position with respect to the first target prediction, hence Eq. (2) is represented as:

$$\vec{A}_1 = \vec{A}_\alpha - \left(\vec{X} * \vec{m}\right)$$
$$\vec{A}_2 = \vec{A}_\beta - \left(\vec{Y} * \vec{n}\right) \tag{2}$$
$$\vec{A}_3 = \vec{A}_\delta - \left(\vec{Z} * \vec{i}\right)$$

Here A_1, A_2, and A_3 are the new vector position of wolves which are recognized as α, β, and δ wolves. m, n, and i indicate the new recalculated distance between wolf and target, X, Y and Z indicate the co-efficient vectors.

To predict on objective of predicting the number of targets involved in search, f(x) as shown in Eq. (3).

$$f(x) = \sum_{i=1}^{M} \left(\vec{A}_i \cdot \frac{\sum_{j=1}^{N} \vec{X}_j * \vec{d}}{M} \right) \tag{3}$$

where N indicates the total number of wolves involved in search and prediction while M indicates the total number of targets available for prediction (customer churn in this discussion).

The prey is attacked by wolves ready to attack by encircling and predicting the optimal prey solution in a search space which is discussed in Eqs. (1) and (2). Grey wolves predicting location of prey and attacking the targets based on position vector of prey predicted while other wolves move their location or position based on the next best optimal solution required. The flowchart (Fig. 4) discusses on the process of prey encircling and capturing.

The objective function is considered to tune the food hunting and prey as target controller parameters using CUPGO algorithm. The fitness function or objective function (F(x)) is defined as:

$$\mathrm{F(x)} = \left\{\alpha_{\max}, \rho, C_w, C_e, C_k\right\} \tag{4}$$

Figure 4 depicts the flow chart of execution of CUPGO approach over Grey Wolf Optimization with K-means nearest neighbourhood selection approach. The execution depends on iteration of αmax, a variable limit which defines the maximum expected outcome of accuracy of churn observed. CUPGO updates customer purchase behaviour, products purchased, time of purchase which adopts vital role as feature analysed to predict customer churn.

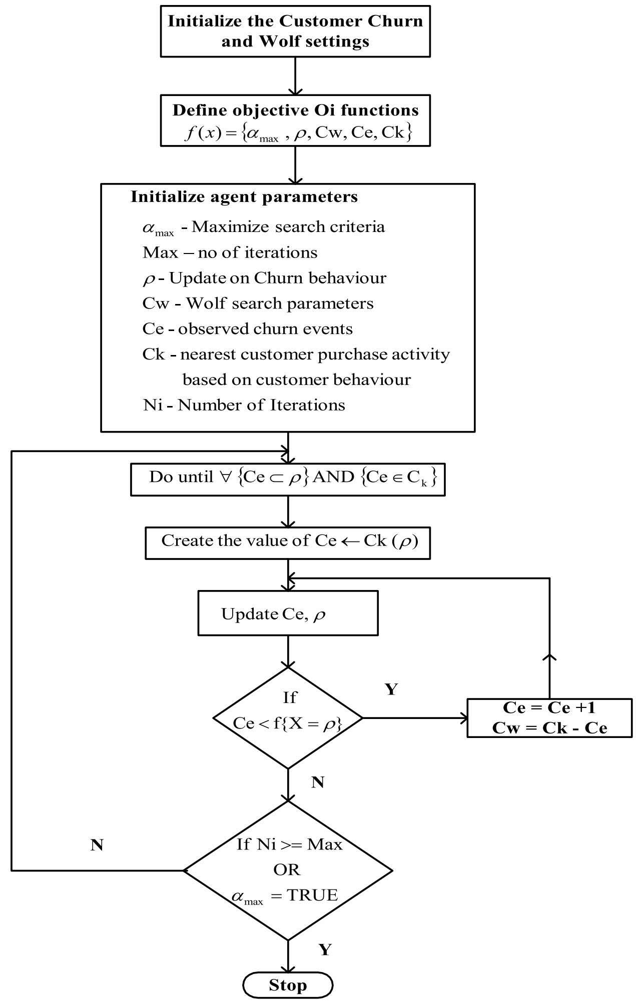

Fig. 4 Flowchart indicating GWO

4 CUPGO algorithmic design

This section defines on the design of Grey Wolf Optimization approach for prediction of customer churn over a business institute. The behaviour of Grey Wolf in hunting its prey as part of food foraging behaviour is major concern for analysis. Predicted the customer churn is depicted as food for Grey Wolf and the process of hunting is depicted as predicting the churn and reason for churn. The process of detecting various abnormal behaviour of customer with reference to distinguishable patterns in customer product purchase datasets can be considered as anomaly detection or outlier detection which is the major discussion of this research.

```
    Objective Function f(x), Xi (i=1,2...n) // Calculate fitness of each customer search criteria

Step 1: Initialize wolf population Cw (w=1,2,...n), n being the number of decision variables whose pulse frequency
Cp at Xi, Initialize pulse rate ri, such that ri is dependent on Cp
Step 2: // define slack variables
Cf : customers buying pattern
Ce : Observed Customer churn events
Ck : nearest customer churn pattern observed
Cw : worst vector observed, based on wolf based behaviour – customer churn
Gk : Customer and product purchase event matrix (nrow x ncol) whose weight is an eigen vector
Step 3:
Create Ck;
Step 4:
for i = 0...(nrow -1) do
for j = 0 …(col-1) do
    Gk[i][j] ← Cf
    Initialize (Cf, Ck)
    for each Cf do
        Create Ce, where ∀ Ce∈ Cf
        Create Cw, where ∀ Cw ⊂ Cf
endfor
Step 5:
 for i = 0 …(nrow-1) do
 for j = 0 ...(ncol -1) do
     if (Cp (Ce, Ck) < Gk[i][j]) AND (Cw != NULL ) then   // check until all wolf are checked
    begin  // Check on the fitness of customer churn data
        Xi ' ∈  ( Xi^1, Xi^2, …. Xi^n }
      Gk[i][j] ←Xi '
     end
     Cw ← Ck - Ce  // worst customer behaviour update
     Ce = Ce +1

endfor
Step 6:
Ck = Cw +1  // Update wolf behaviour in range with nearest churn pattern
Update Ck, Cw, Ce
```

5 Experimental analysis and implementation

5.1 Dataset

CUPGO algorithm takes into consideration analysis of all active customers who are engaged in retail shopping process observed over more than 2 years of shopping process consistently in business institute. This work considers real customer dataset collected from a retail store over the period of Jan-2017 to Nov-2018 which possess around 12,730 records for 1117 products variable over cost as a differential parameter as shown in Table 1. GWO control parameter values can be set and modified based on execution of Ck recommendations.

Table 1 Dataset property

Attribute density	212
No of records	12,730
Missing values	43%
No of numerical attributes	9325
No of categorical attributes	260

5.2 Results and analysis

This section discusses on performance analysis of CUPGO over traditional computational methods such as ACO, and PSO. The discussion focuses on accuracy rate of early churn prediction rate observed, rate of retention rate, observed error rate and time complexity involved in prediction. Figure 5 shows the observed customer retention rate observed

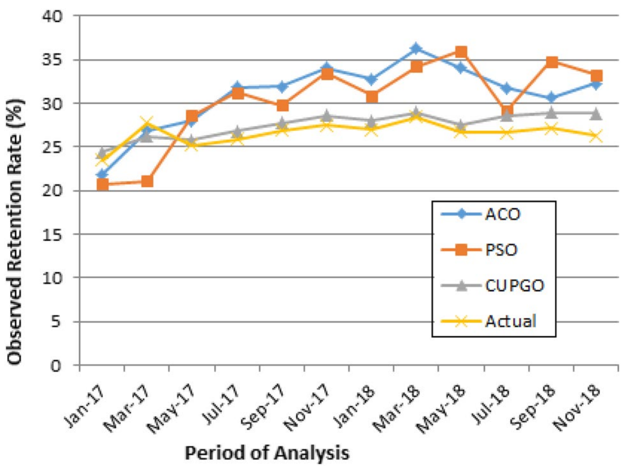

Fig. 5 Observed customer retention rate over CUPGO and other algorithms

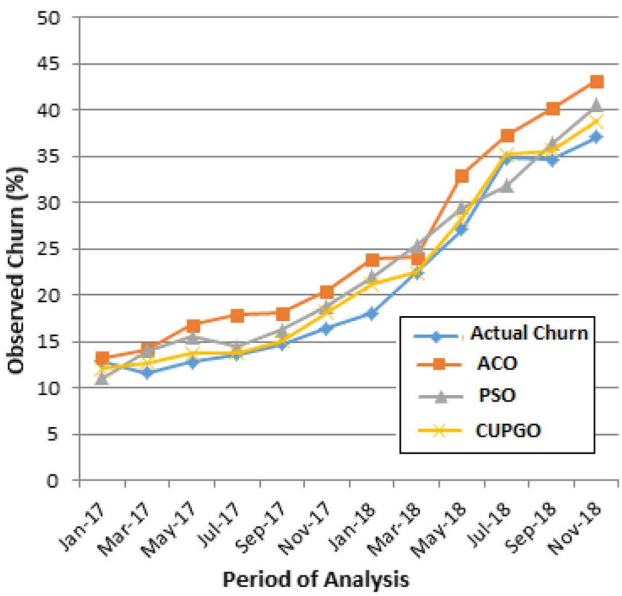

Fig. 6 Analysis of customer churn observed over CUPGO with other algorithms

using CUPGO which involves the customer life time value (CLV) as major parameter for analysis. The percentage of observed retention rate on forecast analysed from CUPGO shows an average variable rate of 34.81% of retention rate in comparison to PSO whose average rate is 27.29% of high fluctuation rate compared over ACO which demonstrates average rate of 26.73%.

The performance of CUPGO shows an optimal similarity to actual observed retention rate with an accuracy rate of 87.25% in comparison to PSO of 76.09% and ACO of 64.29% accuracy. Figure 6 shows the observed churn rate for the period of analysis over 36 months of data collected consistently being analysed for CUPGO and other approaches.

CUPGO performs an improved accuracy of churn prediction over PSO and ACO approaches as shown in Fig. 6. CUPGO shows an average of 25.28% of churn in comparison to actual churn of 26.78% who similarity index of 89.26% match and mismatch of 08.11%. PSO shows 76.92% match of similarity index and ACO shows 62.11% of similarity index match.

The performance of CUPGO is measured over other approaches using the mean absolute percentage error defined in terms of observed chance of error over the assigned data used for analysis as shown in Fig. 7. Mean Absolute Percentage Error is an analytical performance metric which indicates the chances of minimal chances of error observed. MAPE also supports in improving of measure of accuracy of forecasts. The MAPE is analysed using the Actual Observed Value (AV) and Forecasted Value (FV) using Eq. 5 as shown below.

$$\mathrm{MAPE} = \left(1/n \sum_{i=0}^{n} \frac{|AV_i - FV_i|}{|AV_i|}\right) \times 100 \quad (5)$$

Table 2 shows the percentage of error observed over CUPGO approach between the actual and forecasted measure, calculated using Eq. 5 whose mean is lesser compared to ACO and PSO. CUPGO shows a better performance as measured from accuracy analysis compared to other computational schemes in terms of churn analysis and retention rate.

CUPGO approach adopts customer churn prediction using Grey Wolf Optimization computational models over neighbourhood k-means analysis approach which involves variable parameters of purchasing activity of customer is analysed. The primary objective of CUPGO involves on early prediction customer churn, which involves time complexity as a major factor in prediction. The above Fig. 8 depicts

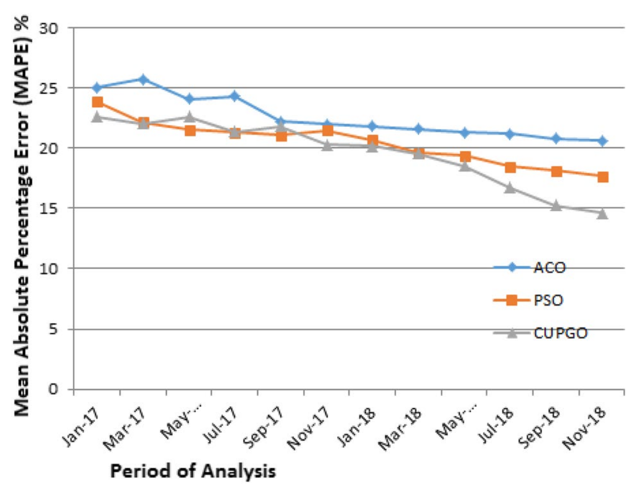

Fig. 7 % of MAPE observed over CUPGO with other algorithms

Table 2 MAPE observed for CUPGO: mean—18.0733

Month	Actual measure	Forecast measure	Absolute % error
Jan-17	112.3	124.7	11.03
Mar-17	108.1	103.3	4.2
May-17	148.9	116.4	21.5
Jul-17	117.3	78.5	33.01
Sep-17	121.7	84.2	39.2
Nov-17	101.3	87.04	20.04

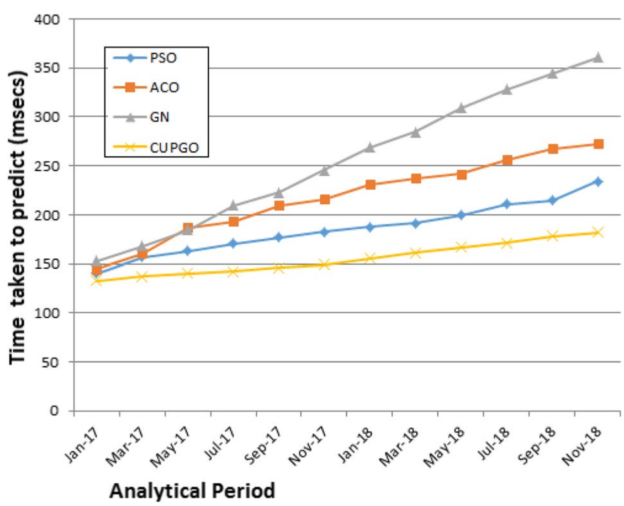

Fig. 8 Time taken for prediction

the performance of CUPGO approach on comparison with ACO, PCO and GA. CUPGO performance shows an average of 155.20 ms of prediction time for the observed period of analysis from Jan-2017 to Nov-2018, while PSO shows its average performance as 185.68 ms, and the average prediction rate of ACO is 218.76 ms and GN shows 256.27 ms. CUPGO, an improved version of GWO with k-nearest neighbour approach demonstrates minimal time taken to predict on churn compared to other analytical approaches.

Customer churn analysis and support over retention schemes requires demandable accuracy among research community. Customer churn is a common challenge noticed in any business institute and the need for an early prediction is required among the community. Predicting the reasons for churn and its analysis includes the behaviour of purchasing a product as a major parameter for analysis along with cost of product, demographic metrics of product as common metrics.

6 Conclusion

CUPGO is designed over Grey Wolf Optimization approach which is largely considered by research community to predict and suggest on large set of target sources being considered as prey. Hence, CUPGO adopts GWO to predict customer churn analysis along with improving customer retention. Retention is a major approach to bring back a customer who gives an indication or suppose to work on late churn in any business organization. Retention suggests methods to retain the customer and suppose to engage methodologically over a month inspite of being opposed to predict an early churn. This approach minimizes the cost involved in bringing back the customer and hence considered as a valuable strategy.

The research outcome concludes on the following objectives resolved:

(a) Inspite of suggesting on customer churn as a metric to decide on outcome of a business institute, this research works suggest on the much neglected feature of customer retention, which minimizes the cost and time involved in bringing the customer as an asset.
(b) Major research work supports on customer churn using traditional data mining algorithms and machine learning techniques, but this work suggests on Grey Wolf Optimization as a soft computational approach along with neighbourhood churn prediction in order to clue on churn much earlier as an early choice of prediction.
(c) An improved accuracy measure in prediction of customer churn rate is shown by CUPGO, being implemented using NumPy based Python code. This approach monitors and checks on performance of distance based metric as classifier over GWO. This work discusses on adopting traditional models such as PSO and ACO algorithms along with GWO to understand the CUPGO's performance.

Future work demands on usage of machine learning algorithms which may improve the accuracy of prediction rate. Inspite of customer behaviour as a metric, future works may also include metrics such as Customer Lifetime Value (CLV), Customer Satisfaction Score (CSAT) which can be obtained as feedback.

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