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Zakat Management System with Allocation Prediction Using Case-Based Reasoning

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ABSTRACT

Zakat has become one of the vital opportunity to be given to the poor and needy. However, there are problems faced by the institution of zakat with the inefficiency and inaccurate issue, especially in the zakat allocation and distribution aspects. Moreover, the zakat allocation and distribution process is time consuming due to the variety of the criteria to be considered, especially when it involves an educational institution. Since the problem usually originates from the organization of zakat itself, it is essential to minimize the difficulties so that zakat can be distributed in a proper way to the qualified person with a suitable allocation. Therefore, the purpose of this project is to develop a web-based Zakat Management and Allocation Prediction System using Case-based Reasoning(CBR) technique. The proposed method consists of two components: (1) Web-based zakat management system which aims to properly manage all related data of the zakat applicant, and (2) Zakat allocation module using CBR to suggests the allocation amount of zakat by finding the similarities between the previous cases and the new cases. For the prediction purposes, the significant main features are identified and suitable weightage is assigned to be able the CBR engine to produce a suggestion. Experimental results using real data collected from UiTM(Perak) Tapah Campus show that our proposed model achieves a significant improvement in the efficiency of managing and allocating the amount of zakat.

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1. Introduction

Islam as the way of life has taught its believer to be humble by sharing the sustenance among the needy people through zakat. One of the main objectives of zakat is to achieve socio-economic justice [1]. Paying zakat is a major religious duty which is one of the five pillars in Islam and is expected to be paid by all practising Muslims who have surplus wealth and earnings [2]. The functions of zakat also include religious, economic and social aspects, which applies the concept of tolerating and the attitude of sharing with others. By paying zakat, it will ease the burden of the poor and needy in facing their difficulties.

Zakat transaction involves two types of people. The first one is *Muzakki* which are the zakat payers. The payers are referred to the Muslims that have an extra amount of income based on the regulation provided by the rule of zakat. The other one is *Mustahiq* which are the person who supposed to be the recipient of zakat [3]. The beneficiaries who are qualified for zakat have the right towards it, and all Muslims in the *Muzakki* category should realize their duty towards the poor and needy. Zakat also can prevent from selfishness because from the zakat, Muslim can learn to be concerned towards other people.

Zakat can be distributed in person or through the people who collect the zakat called *Amil*. However, since there are rules and criteria to be considered for the selection of Mustahiq, some problem has been reported in zakat organization management. The problems include the management of *Muzakki* and *Mustahiq* data, the record of zakat collection, validation of zakat and also the allocation of zakat amount. Essential to be realized, the issues appear to be more serious when they involve education institutions where the focused *Mustahiq* are the students. For this kind of institutions, specifically at UiTM (Perak) Tapah Campus, the allocation of zakat is depending on the amount of zakat allocated by the management. Therefore, the amount of zakat they received might be different for each semester due to more situations and criteria to be considered for both qualified Mustahiq and the zakat amount received by the institution for the current semester.

Under those circumstances, this research is conducted to focus on zakat management and allocation prediction system for the students. The proposed method consists of two components: (1) Web-based zakat management which aims to manage all related data of the zakat applicant properly, and, (2) Zakat allocation module using Case-based Reasoning (CBR) to suggests the allocation amount of zakat by finding the similarities between the previous cases and the new cases.

2. Literature Review

The research area of this project is the zakat management system that manages related data to predict the allocation of zakat using the CBR approach. We discuss the literature into two subsections: (1) zakat management system and (2) prediction approach.

2.1 Zakat Management System

Zakat institution has the most significant role in collecting and also distributing zakat to the recipient[4]. Zakat is collected from various kinds of resources. Muslim that has an extra income need to pay zakat to fulfil their responsibilities. Zakat transaction involves two types of people, which are payers of zakat (*Muzakki*), and the recipients (*Mustahiq*) of zakat. Nowadays, zakat management system that provides the services of zakat application and distribution system already exists. This section describes the difference between Zakat Perak, Zakat Selangor and Zakat Terengganu in terms of the services provided.

Zakat Perak is the official system from Majlis Agama Islam Dan Adat Melayu Perak (MAIAMP) developed by Perak Team. This system provides several modules including zakat payment, zakat calculator and also the application of zakat for the student based on their level of studies for the admission assistance to public or private higher education institution (IPTA/IPTS). This system also provides a service in collecting zakat through Financial Processing Exchange (FPX) called eZakat. Besides, this system offers a service of the zakat scheduled deduction system and even online transaction statistics.

Another institution is Zakat Terengganu, which has an official system developed to organize the collection and distribution of zakat properly. This system provides a distribution of zakat among people who lives in Terengganu, zakat collection, cash Waqaf Scheme, rental premises and also zakat calculator. Besides, an online zakat application is also provided.

Meanwhile, zakat Selangor also has an online system to organize the zakat payment and collection called eZakatONLINE. The system provides services of online zakat payment through FPX, zakat calculator, zakat application and status checking. There are more related information can be found from this system, such as zakat collection and distribution report, and also the activities conducted by the institution. They also provide zakat assessment services. Table 1 shows the comparison of functions for the Zakat Perak, Zakat Terengganu, Zakat Selangor and the proposed system.

Table 1. Comparison of the existing system and the proposed system

Function	Zakat Perak	Zakat Terengganu	Zakat Selangor	Zakat Allocation Prediction System
Zakat Scholarship	Yes	Yes	No	**No**
Zakat Application for Student	Yes	Yes	Yes	**Yes**
Online zakat collection using FPX	Yes	No	Yes	**No**
Zakat Calculator	Yes	Yes	Yes	**No**
Zakat Prediction Allocation	No	No	No	**Yes**
Zakat Distribution	Yes	Yes	Yes	**No**
E-Zakat Account	Yes	No	Yes	**No**

From the observation of the three systems so far, an automatic allocation for the amount of zakat to the zakat recipients still not available. All the existing systems are focussing on the zakat online payment and application only. Therefore, this project is proposed to use the CBR approach to test whether it can be implemented well to predict the allocation of zakat to the student.

2.2 Knowledge-based and prediction approaches

Tripathi [5] define the knowledge-based as an expert system which involved human intelligence for solving a problem. Knowledge-based contains skill from a combination of many experts for solving problems in the computer system. Therefore, the knowledge-based system can be defined as a computer program that involved the behaviour and judgement of a human and behaviour from experience in a specific field.

The characteristic of knowledge-based includes a high-quality performance that is provided to solve a complex and challenging problem. The output can be better than or same as a human expert. Next, to guide reasoning, a heuristic is applied in an expert system so that the search area of the solution is reduced. The details of the expert system contain a unique feature that gives a capability for an expert system to review for its decision and own reasoning [5].

According to [6], the inference engine is one of the components in the knowledge-based system. The inference engine is defined as a software program which contains the availability of knowledge in a knowledge-based system. It is like the brain of an expert system where it plays a significant role as an interpreter in analyzing the rules. Explanation and reasoning state all the action by the system. It can be explained on how the solution is provided. Reasoning in the knowledge-based approach includes rule-based reasoning, case-based reasoning [7][8][9], constraint-based reasoning and hybrid between approaches. The are various works implementing these reasonings, such as [10],[11], [12], and [13] show a significant result in the various related domain.

According to [14], case-based reasoning is defined as a method of creating a knowledge-based system for retrieving and reusing a solution based on a similar solution in the previous work. A problem or a new case is defined as a case without a solution. The use of CBR that begins from the past solution for the problem that are similar to other cases is said to be more efficient compared to the solutions that are going to be generated from the beginning [15]. Once a problem is solved, it can be used in the future as it is retained as a new case.

CBR has been classified accordingly to the use of reasoning itself. Basically, CBR is categorized into two types which are interpretive CBR and problem-solving CBR [16]. Interpretive CBR is implemented when a previous solution can be used for the new cases according to the differences and similarities between the two cases. Otherwise, the aim of problem-solving in CBR, is to create a solution from implementing the previous cases. It is said to have an efficient result when the two types are combined.

The result generated from the CBR reasoning is similar to the prediction process. The prediction is focused on estimating the value of specific attributes based on the importance of other features. The attributed values to make a prediction is usually referred to as a target or the dependent variables. Prediction is mostly known as the explanatory or independent variable. CBR, as one of the reasoning techniques, is implemented to produce predictions in the proposed system.

3. Methodology

This section introduces the proposed system architecture for zakat management and allocation prediction using case-based reasoning technique to be validated with the available data from UiTM (Perak) Tapah Campus.

The system architecture of zakat allocation prediction using CBR is shown in Figure 1. We collected the existing manual data from zakat management to be organized as existing cases. We then start with the pre-processing of raw data to be arranged accordingly to the standard input data for the proposed system. Significant features have been identified in order to model the proposed framework. These features are used as the main component for the prediction using CBR. The identified features are then fed to the CBR engine. The new cases are compared to the existing cases, and the best match cases are then proposed as the recommended solution. The inference engine then learns of the fail or success solutions. If there are more than one cases match the new cases, then the ranking method is applied.

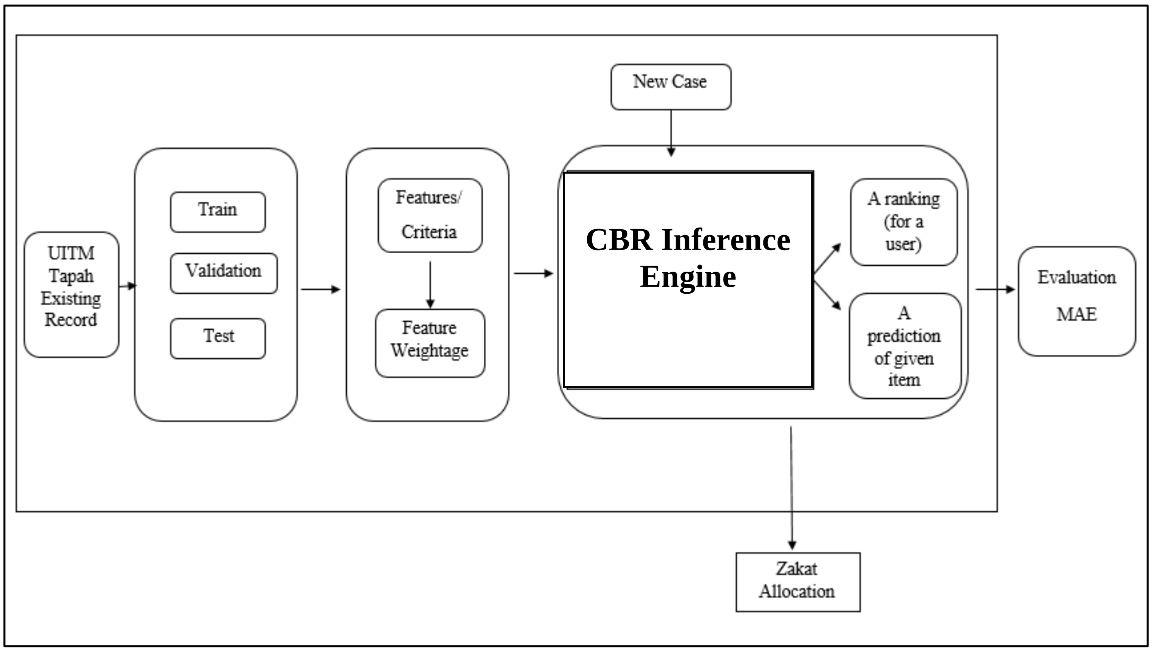

Figure 1. System architecture for zakat allocation using CBR

Based on previous research by [17], the similarity is the core concept in CBR. The similarity is often used in case adaptation and case retrieval, and also in the case building. This measure the similarity between two data. When the data are more similar, the value is higher.

K-Nearest Neighbour or k-NN is defined as a simple algorithm that is used to find a similarity. K-NN algorithm searches for the closest value. It also stores all the cases that are available based on their similarity measure. The k-parameter specifies how many nearest neighbours are considered. The closeness is defined by the difference, which is called a similarity measure. According to [17], k-NN holds a significant role in CBR. This project used k-NN because the implementation of k-NN is simple, and k-NN does not have a training period. Since k-NN does not require a training period as compared to others, it is more reliable and faster in the implementation[18]. In this research, the similarity measure of k-NN is applied. The formula of k-NN is shown in (1)

$$\frac{\sum_{i=1}^{n}(w_i) \times \mathrm{sim}(f_i^1, f_i^R)}{\sum_{i=1}^{n}(w_i)} \qquad (1)$$

Based on (1) the weightage, *w* is assigned in each element of the attribute in order to find the best match or most similarity between the previous cases. For this research, k-NN is used in the inference engine as its similarity measure while retrieving the best match cases.

4. Experiments and results

These sections present the experimental detail of our proposed framework. We start with a detailed analysis of the dataset, followed by experimental settings and the mechanism used to implement and evaluate the proposed framework.

4.1 Dataset

This project uses 50 completed cases collected from UiTM(Perak) Tapah campus. The data has been divided into two, which are the test cases and old cases. 8 test cases are separated from the existing cases, while the other 42 cases are used as the old cases to be compared with the new case.

This project originally contains 36 features of zakat applicant. The detail can be divided into two sections: (1) student background and (2) current educational detail. From all of the 36 features, the dimensional reduction is applied in order to reduce the computational complexity. Based on the interview with the UiTM staff who handle the zakat selection processes, significant features selection is done. As a result, only five essential features have been selected for zakat allocation purposes. The five essential features are parent-sponsor, house-rental, education-loan, self-need and campus-transport. These features are called main features. Table 2 shows the five main features of the dataset decided based on the advice of the expert. The range of the feature selection is based on the actual data of the collected cases. Based on the range of the features selected, the weightage is assigned based on the settings. This research uses three different settings to compare which one produced better results of prediction.

Table 2. Selected main features from expert advise

Main features	Value Range
parent-sponsor	0-2000
house-rental	0-2000
education-loan	0-2500
self-need	0-1500
campus-transport	0-900

4.2 Experimental Setting

We manage to set up three different settings for experimental purposes. The differences between each setting are the range of input value with the different assignment of weightage for all the main features. This means, each setting consist of five main features with different range and weightage. The weightage is very crucial in order to determine the best match cases in the similarity measure. Table 3 (a-e) shows the three different weightage setting for the main features of zakat allocation prediction.

The range for each setting is assigned based on the difference of the test case compared to the old cases. The first setting uses the three division of range that contains the same weightage for the features. The second setting uses the five-division of the range that contains the different weightage for each range. The last setting uses different randomized range and different weightage.

This project uses a different setting to decide which setting can produce a better result for the allocation. The purpose of assigning the range in a specific weightage is to retrieve the best match cases to be recommended. The process chooses the most suitable cases from the top-ranking that match the features.

Table 3. Three weightage settings for the five main features of zakat allocation prediction.

(a)

Parent-Sponsor	
Range	Weightage
Setting 1	
0-500	0.6
501-1000	0.3
1001-1350	0.1
Setting 2	
0-300	0.35
301-600	0.3
601-900	0.2
901-1200	0.1
1201-1850	0.05
Setting 3	
0-500	0.4
501-1000	0.3
1001-1500	0.2
1501-1850	0.1

(b)

Accomodation	
Range	Weightage
Setting 1	
0-300	0.6
301-600	0.3
601-900	0.1
Setting 2	
0-200	0.05
201-400	0.1
401-600	0.2
601-800	0.3
801-900	0.35
Setting 3	
0-200	0.45
201-400	0.3
401-500	0.15
501-900	0.1

(c)

Educational-Loan	
Range	Weightage
Setting 1	
0-500	0.6
501-1000	0.3
1001-1350	0.1
Setting 2	
0-500	0.35
501-1000	0.3
1001-1500	0.2
1501-2000	0.1
2001-2500	0.05
Setting 3	
0-500	0.4
501-1000	0.35
1001-1500	0.15
1501-2000	0.07
2001-2500	0.03

(d)

Self-Need	
Range	Weightage
Setting 1	
0-500	0.6
501-1000	0.3
1001-1350	0.1
Setting 2	
0-300	0.05
301-600	0.1
601-900	0.2
901-1200	0.3
1201-1350	0.35
Setting 3	
0-500	0.7
501-1000	0.2
1001-1350	0.1

(e)

Transportation	
Range	Weightage
Setting 1	
0-300	0.6
301-600	0.3
601-825	0.1
Setting 2	
0-180	0.05
181-360	0.1
361-540	0.2
541-720	0.3
721-825	0.35
Setting 3	
0-225	0.65
226-450	0.2
451-675	0.1
676-900	0.05

4.3 Evaluation Metric

The evaluation metrics used to measure the correctness of the proposed prediction method are Mean Squared Error (MSE) and Mean Absolute Error(MAE). MSE is an average square of "errors". MSE measure of prediction requires the prediction goal, and a predictor is said to be the data function. (2) is the formula on calculating MSE.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - X_i)^2 \qquad (2)$$

Mean Absolute Error (MAE) measures the error of average magnitude from a prediction by ignoring their direction. (3) is the formula on calculating MAE.

$$MAE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \qquad (3)$$

5. Result and Discussion

In this section, we discuss the findings observed based on the experimental performance of different setting stated in section 4.2. Table 4 shows the result of the best match cases for experimental Setting 1. From the table, the highest difference is from case 14 and 40. The total similarity for the two cases is 3, where the similar cases for case 14 are case 8 and 9 and for case 40 is from the cases of 9. The difference between the actual and predicted value for case 14 is 142, and for the case 40 is 99. This value shows the largest number of differences between the actual and predicted value. For the case of 20 and 32, the value of predicted is exactly the same as the actual value, which is 284. So, for this setting, the prediction is assumed successful as the result of the predicted value is exactly the same as the actual result for the two cases.

Table 5 shows the result of the best match result for experimental Setting 2. From the table, the highest difference in this setting is from case 10 and 27. The total similarity used for this case is 1.05, where the similar cases for case 10 are case 8 and for case 27 is from case 7 and 48. The difference between the actual and predicted value for case 10 is 271, which for case 27 is 105. For this setting, there is no predicted value with the same actual value from the previous cases. The differences in the rest 8 test case have the average value which can be accepted, where the range is from 28 to71.

Table 6 depicts the results of best match cases for Setting 3. From the table, it states that the case of 10, 14, and 40 has the highest difference value of prediction. The total similarity used for this case is 2.35, 3, and 2.6. The difference between these three cases involved the value of 142 and 99, which is from the previous cases of 8 and 9. For case 20, the actual and predicted value is exactly the same as the actual value which there are no differences between them. As for the other cases, the differences are in the average range between 29 and 43.

Table 4. The best match cases for Setting 1

Case ID	Pemberian Ibubapa	Rumah Sewa	Pinjaman	Keperluan Kendiri	Pengang-kutan	Total similarity	Similar cases	Actual Value	Predicted Value	Difference	Average
10	1400	700	1800	250	300	2.7	OLDCASES 50	142	**100**	42	100
14	500	625	2380	250	300	3	OLDCASES 8 OLDCASES 9	142	**284**	142	262.5
16	500	750	1780	250	300	3	OLDCASES 12 OLDCASES 50	241	**199**	42	149.5
20	250	2375	900	250	300	3	OLDCASES 8 OLDCASES 9 OLDCASES 50	**284**	**284**	**0**	208.3
27	150	1300	560	150	300	3	OLCASES 12 OLDCASES 47	255	**199**	56	241.5
32	300	2400	615	250	450	3	OLDCASES 8	**284**	**284**	**0**	284
40	600	2500	750	350	75	3	OLDCASES 9	142	**241**	99	241
46	400	1800	352	250	300	3	OLDCASES 12 OLDCASES 50	241	**199**	42	149.5

Table 5. Best match cases for Setting 2

Case ID	Pemberian Ibubapa	Rumah Sewa	Pinjaman	Keperluan Kendiri	Pengang-kutan	Total similarity	Similar cases	Actual Value	Predicted Value	Difference	Average
10	1400	700	1800	250	300	1.05	OLDCASES 38	142	**359**	217	359
14	500	625	2380	250	300	1.15	OLDCASES 21 OLDCASES 31 OLDCASES 37	142	**213**	71	147
16	500	750	1780	250	300	1.1	OLDCASES 21 OLDCASES 31 OLDCASES 36 OLDCASES 37 OLDCASES 48	241	**213**	28	136.6
20	250	2375	900	250	300	1.2	OLDCASES 21 OLDCASES 31 OLDCASES 36 OLDCASES 37 OLDCASES 51	284	**213**	71	128.2
27	150	1300	560	150	300	1.05	OLCASES 7 OLDCASES 48	255	**360**	105	251
32	300	2400	615	250	450	1.25	OLDCASES 21 OLDCASES 31 OLDCASES 37 OLDCASES 51	284	**213**	71	135.3
40	600	2500	750	350	75	1.1	OLDCASES 4 OLDCASES 21 OLDCASES 37	142	**184**	42	175
46	400	1800	352	250	300	1.05	OLDCASES 4 OLDCASES 7	241	**184**	57	272

Table 6. Best match cases for Setting 3

Case ID	Pemberian Ibubapa	Rumah Sewa	Pinjaman	Keperluan Kendiri	Pengang-kutan	Total similarity	Similar cases	Actual Value	Predicted Value	Difference	Average
10	1400	700	1800	250	300	2.35	OLDCASES 8	142	**284**	142	284
14	500	625	2380	250	300	3	OLDCASES 8	142	**284**	142	284
16	500	750	1780	250	300	2.25	OLDCASES 8	241	**284**	43	284
20	250	2375	900	250	300	2.6	OLDCASES 8	**284**	**284**	**0**	284
27	150	1300	560	150	300	2.35	OLCASES 8 OLDCASES 18 OLDCASES 33	255	**284**	29	246
32	300	2400	615	250	450	2.23	OLDCASES 18 OLDCASES 24 OLDCASES 34	284	**312**	28	347.67
40	600	2500	750	350	75	2.6	OLDCASES 9	142	**241**	99	241
46	400	1800	352	250	300	2.4	OLDCASES 8	241	**284**	43	284

Figure 2 illustrates the comparison of the actual and predicted value for Setting 1. Prediction of the training case in this research is compared with the actual results of zakat allocation amount of the previous cases. Based on the figure, if there are no differences, the case is successfully predicted. For this graph, there is two value that is successful in getting the predicted value where it is exactly the same as the actual one, which is 284. The highest differences between the actual and predicted value also appear in the graph where the differences are about 142 and 99. The other cases produce the average value of the actual value that can be accepted because their differences are not too large.

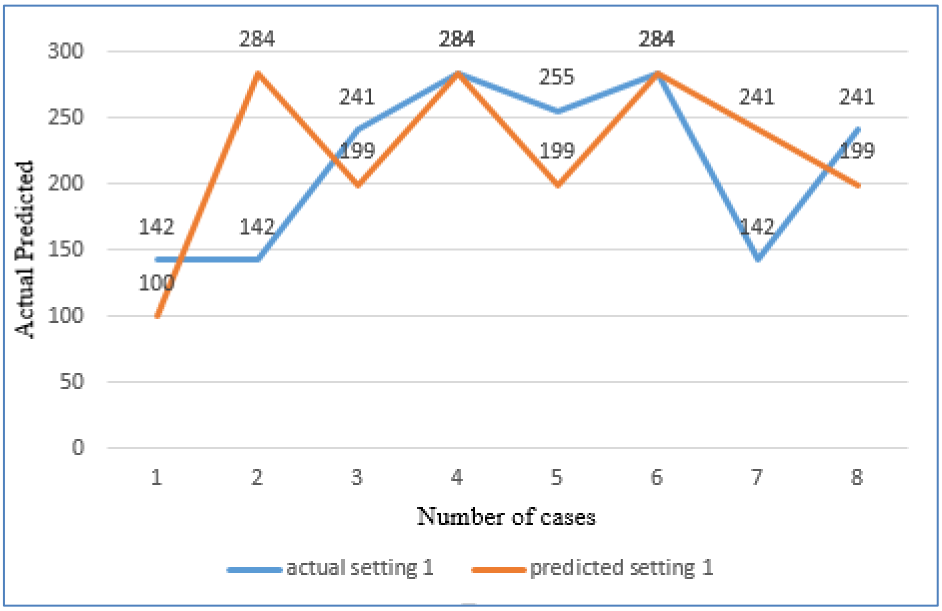

Figure 2. Differences between actual and predicted value for Setting 1

Figure 3 shows the differences between the actual and predicted value for Setting 2. The actual and predicted value is compared to find which setting produces the least difference in order to be selected to be used in making a prediction of the allocation amount. Based on the figure, there is no predicted value which produces the same output as the actual value. Based on the result, the first cases shows the highest difference of prediction where the actual value is 142, and the predicted value is 359, with the different value is 217. Case 5 also shows the highest value of prediction, where the difference is about 105. The lowest case is case 2, where the difference is only 28. The other cases have an average value of difference which is between 42 and 71.

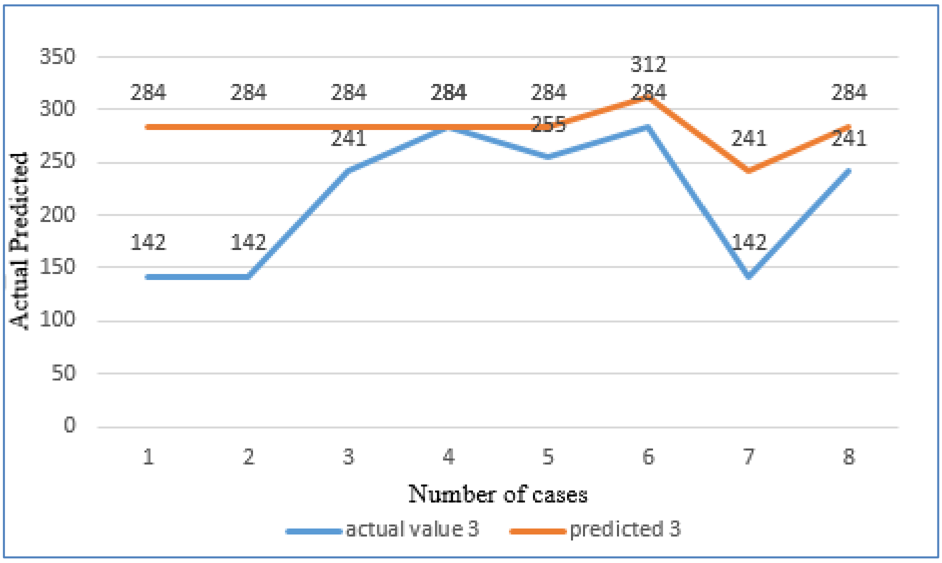

Figure 3. Differences between actual and predicted value for Setting 2

Figure 4 depicts the actual and predicted value for Setting 3. Based on the result, there is a value which is exactly same as the actual result. The predicted value of case 4 is the same as the previous Setting 1, which is 284. Based on this result, the largest difference is from case 1, 2 and 7 where the difference is 142, 142, and 99. The case that has the lowest differences among the others are in case 5 and 6 where the difference is 28 and 29. The other case has the average number of differences which range is 43.

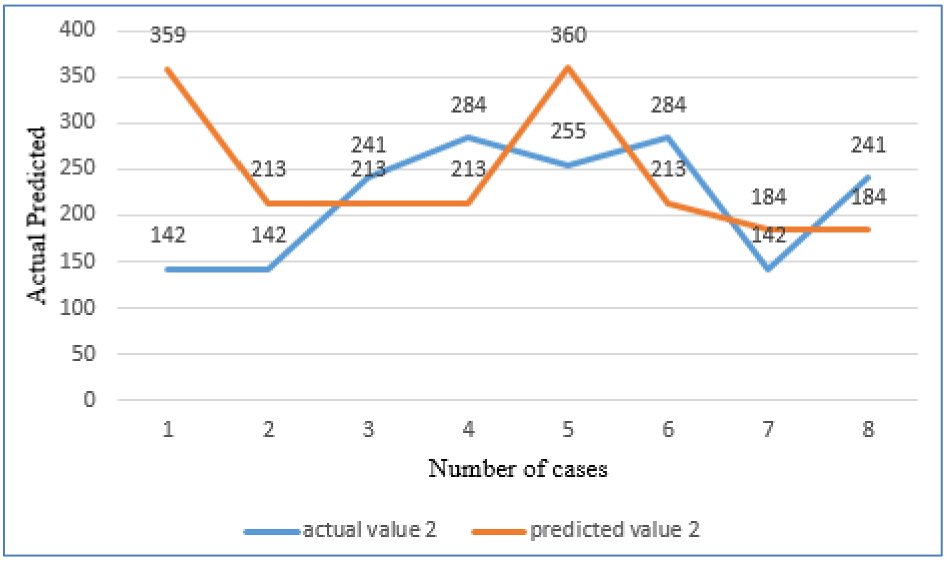

Figure 4. Differences between actual and predicted value for setting 3

Figure 5 illustrates the difference between Setting 1, 2, and 3. Based on the result, Setting 1 has the lowest difference compare to setting 2 and 3. From Setting 1, the predicted value that was exactly the same with the actual value comes from two cases which is case 4 and 6. Based on the figure, Setting 3 has the largest difference between the three setting and Setting 2 has an average difference. The MAE for Setting 1 is the smallest, which is 52.875 followed by Setting 3, which is 65.75 and followed by Setting 2, 82.75. Even though Setting 2 has the largest difference between the three settings, Setting 2 has the exact match to the actual for case 4. As a conclusion, the predicted value of the exact match the actual value effect the MAE for each setting.

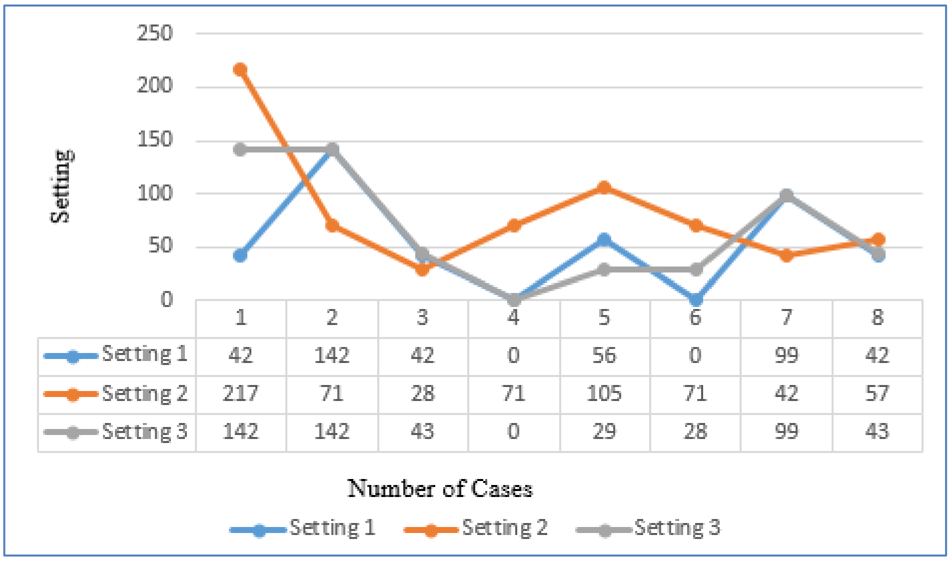

Figure 5. Differences between settings

Figure 6 depicts the MAE for three settings used in predicting zakat allocation. Based on the result, Setting 2 is selected as the critical one because of the highest MAE among the three cases. The second case is Setting 3, the middle value of in terms of MAE, which is 65.75. The third case is Setting 1, which is the smallest of MAE among the three settings, which is 52.875.

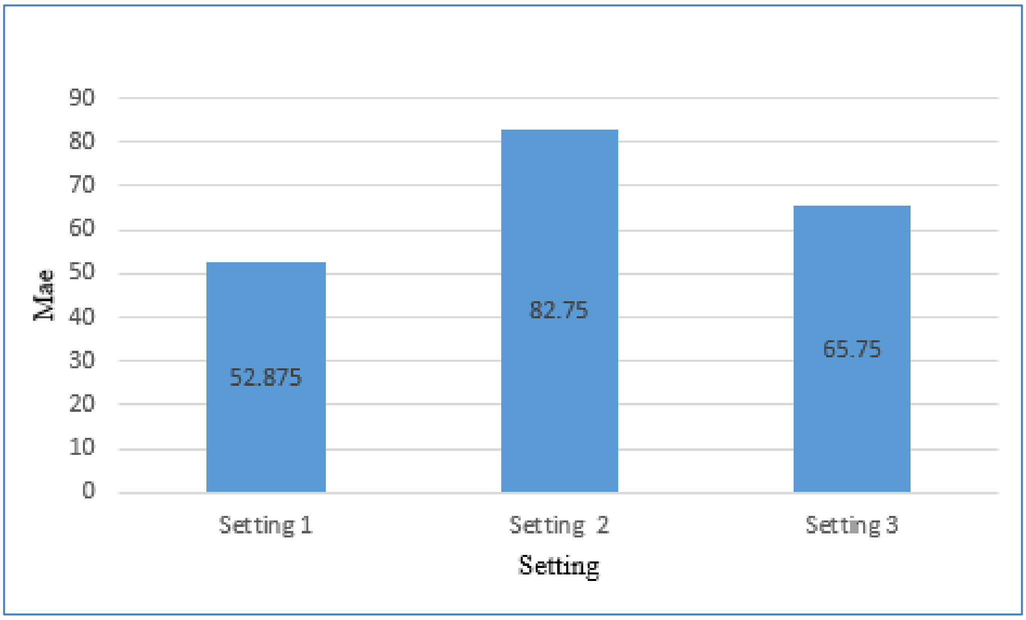

Figure 6. MAE for the three settings

Based on the result, it is observed that the largest of weightage range is set, the smallest the MAE produced. For Setting 1, the weightage is in the range of 2.7 to 3 while for setting 2, the weightage used is in the range of 1.05 to 1.25. The weightage of the third setting used in this research is in the range of 2.23 to the range of 3.

Based on the weightage states for each setting used, the most considerable weightage used for Setting 1 produces the lowest MAE and the smallest weightage used in Setting 2 make the largest of MAE. In this case, the weightage of Setting 1 is selected as the proposed method in Zakat

Allocation Prediction System. Therefore, Setting 1 is chosen as the best setting according to their MAE in predicting the zakat allocation amount for each student.

6. Conclusion

The objective of this project is to develop a Zakat Management and Allocation Prediction System using Case Based-Reasoning. This project is focusing on suggesting the allocation of zakat amount for the student in UiTM Tapah using the Case-based Reasoning approach. CBR approach has been implemented to allocate the amount of zakat for the student. Steps in CBR involved are retrieved the most similar cases, reuse the information and knowledge, attempt to solve the problem and provide a solution to the problem. For this project, there are three types of user involved. They are (1) students, the person that is going to make an application of zakat, (2) the staff that are going to make approval of zakat application and, (3) the admin, which are going to accept the approval of registration from student and staff. The contribution that has been made by this system is to help staff in deciding the allocation of zakat amount for the student without need to discuss with all the members of zakat. So, this system can reduce the time for both staff and other members, and the staff does not need to use their manual ways to allocating the zakat for students. However, there is some limitation in this system which includes the allocation amount of zakat for students is not 100% accurate because of the data collected from the previous cases is only 50 cases as for CBR system, more data will drive to a more precise result. It is hoped that this project will benefit the staff or anyone responsible for this task. For the future, there is more advance, and recent prediction methods to be investigated, such as machine learning that is suitable for this domain.

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