Soft Set Decision/Forecasting System Based on Hybrid Parameter Reduction Algorithm

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***Abstract*—Existing classification techniques, which are previously proposed for eliminating data inconsistency, could not achieve an efficient parameter reduction in soft set theory as it affects the obtained decisions. Additionally, data decomposition based on previous algorithms could not achieve better parameter reduction with available domain space. Meanwhile, the computational cost made during the combination generation of datasets can cause machine infinite state as Nondeterministic Polynomial time (NP). Although the decomposition scenario in the previous algorithms detects the reduction, it could not obtain the optimal decision. The contributions of this study are mainly focused on minimizing choices costs through adjusting the original classifications by decision partition order and enhancing the probability of search domain by a developed HPC algorithm. The results show that the decision partition order technique performs better in parameter reduction up to 50%, while other algorithms could not obtain any reduction in some scenarios.**

***Index Terms*—Normal Parameter Reduction; Soft Set; Decision Making; Classification.**

I. INTRODUCTION

Nowadays, redundant data is one of the open issues due to rapid development with technologies. This issue is more visible, especially in decision-making, since the behavior of such type of data results in complexity and uncertainty during the process of decision-making. Besides, the widespread use of technology has resulted in the necessity of extra memory due to the need to make use of storage and produce redundant copies. Thus, it has become a crucial need to reduce such huge amount of data, which require substantial original soft data characteristics to improve the storage. Hence, the reduced data will contribute to the improvement of the efficient search of an optimal decision for a given problem scenario. For this reason, the demands of reducing choices, cost, combinations complexity and the use of memory space have encouraged researchers to develop efficient techniques to address issues related to obtaining optimal solutions. At the same time, these intelligent applications must inherit the characteristic of original soft data.

The issue of data redundancy and the use of its reduction have become a key issue in knowledge management area. Considerable effort has been devoted to developing Knowledge Management Systems (KMS) to capture and manage knowledge through the digital capture, storage and retrievals not only in single location but also in multiple distributions [5]. KMS tried to overcome the replications problems, which are geographically connected as well as to fit original sources in small space instead of data compressions [20], [16], [11], [10] and [22]. The knowledge management has succeeded with the ability of organizing and protecting knowledge in an efficient manner [20]. With the help of original characteristics, mining these repositories can be managed more efficiently [8] and [26].

On the other hand, improving the cost performance of choice is important since economically, it assists customers in their process of decision-making. Besides, it can significantly save their money with the help of obtained optimal choice. This could be achieved when their taken process is rationalizing the cost, and at the same time obtain an output that has characteristics as exactly as the original soft set. The data volume can be managed by information system (IS) [19]. The IS facilitates data management by rapid processing, while the key benefits clearly do not only lay on the process of transmitting and exchanging information anywhere anytime, but their extensive use would result in the complexity and uncertain data. The complexity and uncertain data occur when information contain repetitions, so it is difficult for human to precisely understand their meanings, in which it that could take days to solve such complex problems [25]. Therefore, good IS would produce more consistent decisions, which gives an accurate result with low cost [15].

Normally, IS generates information with the help of Decision Support System (DSS) that distinguishes between the cost of each choice by comparing their advantage and disadvantage. Using DSS as a computer based model, IS is able to solve complex decisions problems significantly [20]. Besides, DSS can infer reasoning to organize and simplify knowledge management, which describes the state of objects in discovering repeated data [3] by using co-relations, such as rules or constraints for long range plan decisions [20]. Through DSS, mathematical models are applied to the computer system as a way to foster the calculations response time and with specific characteristics simplify the decision-making process with prompt response [20]. However, these systems cannot make decisions nor give reasoning since they are normally used for just verifying the data influences [1], without correct and perfect theory. This yields limited results, and from this point, the need for an efficient decision algorithm can overcome this issue, in addition to consistently achieving goals.

Many research studies have developed and viewed in favor of data reduction to ensure high quality and integrity of data before it can be processed in supporting decision-making. In the last decades, several algorithms were developed in the field of data reduction, which are aimed to obtain valuable information. Note that in case of big-data, the reduction process is very important since human being's brain has a limitation in performing decision-making. The human brain is only able to make decisions based on the specific amount of information or choices, but it cannot extend the decision beyond the provided information [9]. As a result, the decision made by the human brain is often not accurate in large data set, thus it is always subjected to uncertainty in the decision-making process [2], [7], [20] and [4].

As has been discussed in the preceding paragraphs, the existing methods of normal parameter reduction in soft set is still utilizing some kinds of manual search, that is, by trial and error process, which could take more time. Furthermore, in case of large data in soft set, it is practically incredible to attain operative reduction. In this regard, the problem solving of normal parameter reduction is considered as one of the combinatorial problems. Thus, the proposed algorithm in this paper is significant to the body of knowledge, which could efficiently maintain the optimal and sub optimal choices during soft set reduction process.

The remainder of this paper is structured as follows. In section II, we present the related works recently proposed in the area of study. Section III introduces the preliminaries of soft set theory and definition, while Section IV discusses the details of the proposed soft set HPC algorithm. The performance analysis is illustrated by Section V, followed by conclusion in Section VI.

II. Related Works

In data reduction, there are two main theories used to manage data uncertainty, which are the rough set and soft set theories. However, this research focuses on soft set theory only as a new way for managing uncertain data in decision/forecasting making process. Soft set theory is also known as binary, basic or elementary system. In addition, soft set may be redefined as the classification of objects in two distinct classes, thus confirming that soft set can deal with a Boolean-valued information system due to differences of multi value language in parameters preferences across the world [20]. Molodtsov in [21] has pointed out that one of the main advantages of soft set theory is that it is free from the inadequacy of the parameterization tools; unlike in the theories of fuzzy set, probability and interval mathematics are visible. Hence, no certain value could be precisely defined to indicate the optimal decision since it is a fuzzy set.

On the other hand, it is important to mention that during data reduction process, it is very crucial to ensure that the obtained reduced sets still consist the original properties and attributes of the information [27], [23]. The main objective of reduction is to lessen the number of parameters, and at the same time, attaining the property of information in helping the process of decision making [23].

In data reduction research area, there are various techniques introduced by researchers, such as [17], [6], [12], [18], [24], [23] and [14]. Every soft set study has verified the influence of parameters exchanges during original combinations generating to search for the exact decisions (solutions); therefore, the direction of reduction is measured by implicitly or non-implicitly conditions. The variation of implicitly or non-implicitly reductions noted that multiple columns yield limited reduction results in the case of uncertainty in the form of non-implicitly. However, there are still issues and challenges in this research area, which give an opportunity for further research to enhance the existing techniques. For example, reduction technique introduced by [17], has an issue of sub optimal problem, which cause inconsistency in the obtained results. This problem of inconsistency from Maji was solved by [6], but the problem of sub optimal decisions still exists, which induce incorrect and inconsistent obtained decision. Thus, to improve the accuracy of the decision making, [12] has introduced the implicitly reduction technique. However, in Kong's technique, in case there is no implicitly, there will not be any reduction and even when there is an implicitly, it has complexity. Hence, the reduction in [12], [13] are considered to be partially achieved. The complexity issue of the proposed technique by Kong has been improved by [24] and [18]. Furthermore, Rose in [23] has introduced a technique for identifying the soft set reduction based on implicitly. In another research, [14] has introduced another technique to reduce the soft data, but without considering implicitly.

To sum up, the existing gaps within all aforementioned algorithms have motivated the researchers to develop a new algorithm that could efficiently predict the optimal and sub optimal decisions through effective and improved reduction technique. Thus, in this research, there are two areas to be explored, which are derived from the above issues in order to address the gaps. The first main issue that needs to be addressed is reducing the data size, while at the same time ensuring the information is in a correct form. The second issue is finding the original features of the information through data classification of optimal and sub optimal decisions that would assist in decision/forecasting making processes.

III. Preliminaries

In this section, a definition of soft set is discussed in addition to an example presents the main concept of soft set theory for normal parameter reduction as well as its proposition.

Definition 3.1 (See [17]. The researchers employed the definitions of a pair (F,E) as a soft set over U, where F is mapping the binary values from the given parameters, as $F: E \rightarrow P(U)$ including the generation of the domain. For any original parameter sub set, their relations are described based on its parameterized family, as $\varepsilon \in E$, $F(\varepsilon)$, which overall is a subset of the universe U and has approximate elements that can deal with or may, instead of a (crisp) set.

Example 3.1. As an illustration, consider the computational domain of a soft set (F,E) determined, such as the "attractiveness of automotive promotions" which describes the preference capabilities that for instance, Mr. X usually aims for when considering the selections to purchase at less price and efficient preference. Assuming the parameters in finite volume have thirty automotive promotion components in the universe U and the propositions are available under the construction, $U = \{p_1, p_2, \cdots, p_{30}\}$, and E was collocated as a set of choices (parameters). In the sub set $E = \{e_1, e_2, e_3, e_4, p_5\}$ all variables were inserted, then the concatenations interpret its meaning, such as e_1 stored the values of "large tire" as the first parameter, e_2 stored the values of "small tire" as the second parameter, e_3 stored the values of "automatic" as the third parameter, stored the values of "manual" as the fourth parameter, e_5 stored the values of "car status" as the last parameter. The validations of this parameter mapping is derived as $F : E \to P(U)$ which described the influence of the given "automotive promotions $(\cdot)$", where $(\cdot)$ is used for choices to be filled in by complete decision. The decision from $e \in E$ categorized in levels is as presented in Figure 1.

$$F(e_1) = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}\},$$
$$F(e_2) = \{p_6, p_7, p_{18}\},$$
$$F(e_3) = \{p_5, p_6, p_7, p_8, p_{12}, p_{13}, p_{14}, p_{15}\}$$
$$F(e_4) = \{p_3, p_5, p_6, p_9, p_{10}\},$$
$$F(e_5) = \{p_1, p_5, p_6, p_7, p_8, p_{10}, p_{11}, p_{14}, p_{15}\}$$

Figure 1: The mapping of parameters of example 3.1[23]

For example, $F(e_2)$ means the automotive promotion for the manual characteristic. The relationships of decision partitions were inferred among parameters as shown in Figure 2. Figure 2 shows the relationship representations, which were established to help soft set algorithms for drop up choices to significant choices and some choices may be negligible.

Thus, we can view and observe the soft set (F, E) as a collection of approximations categorized into similar classes as illustrated in the following:

$$(F,E) = \begin{Bmatrix} e_1 = \{p_1, p_2, p_3, p_4, p_5, p_6, p_7, p_8, p_9, p_{10}\} \\ e_2 = \{p_6, p_7, p_{18}\} \\ e_3 = \{p_5, p_6, p_7, p_8, p_{12}, p_{13}, p_{14}, p_{15}\} \\ e_4 = \{p_3, p_5, p_6, p_9, p_{10}\} \\ e_5 = \{p_1, p_5, p_6, p_7, p_8, p_{10}, p_{11}, p_{14}, p_{15}\} \end{Bmatrix}$$

Figure 2: The decision partitions of soft set based on example 3.1

The information transfer into corresponding preferences is based on a correlation, where "1" will denote as part of the choice, and "0" means it is not part of the choice of the automotive promotion, as shown in Table 1.

The parameters governing the flow are shown in Table 1, with the usage of "1" and "0" determining whether the objects can be part of preferences or not. In the table, the parameter (preferences) flows can be dynamically managed by a Boolean-valued information system. The similar relations found in a soft set and a Boolean-valued information system is identified as follows:

Proposition 3.1. If (F,E) is a soft set the elementary over the universe *U*, then in (F,E) the calculations of a binary-value in information system is determined according to $S = (U, A, V_{\{0,1\}}, f)$ with the obtained results similar to soft set correlation and gives result as shown in the previous table.

Proof. Let (F,E) be a soft set over the universe U, then the mapping configuration is defined as $F = \{f_1, f_2, \cdots, f_n\}$, where the evaluation of two terms of classification (binary) are assumed as $S = (U, A, V_{\{0,1\}}, f)$

Table 1
Tabular of Soft Set 1 Parameters Values from Example 3.1

U/E	p_1	p_2	p_3	p_4	p_5
u_1	1	0	0	0	1
u_2	1	0	0	0	0
u_3	1	0	0	1	0
u_4	1	0	0	0	0
u_5	1	0	1	1	1
u_6	1	1	1	1	1
u_7	1	1	1	1	1
u_8	1	0	1	0	1
u_9	1	0	0	1	0
u_{10}	1	0	0	1	1
u_{11}	1	0	0	1	1
u_{12}	1	0	0	1	0
u_{13}	0	0	1	1	0
u_{14}	1	0	1	1	1
u_{15}	1	0	1	0	1

$f_i : U \to V_i$ and $f_i(x) = \begin{cases} 1, & x \in F(e_i) \\ 0, & x \notin F(e_i) \end{cases}$, for $1 \le i \le |A|$ between any different configurations. Hence, if $A = E$, for any sub set computed by V= $U_{e_i \epsilon A} V_{e_i}$, where total parameters exchange, then a soft set (F,E) correlations can be considered as a binary-valued information system.

IV. Proposed Soft Set HPC Algorithm

Hybrid Parameter reduction Combination (HPC) algorithm has been designed based on Hybrid Parameter Reduction [23] and Parameterization Reduction [14]. The purpose of this combination is to overcome both techniques limitations. The HPC combinations reduce similar relations from objects based on new objects relations. The reduction is achieved based on Hybrid parameter reductions by [23], it removes the implicit assumption, and then deletes objects that have similar representations of parameters, and thus every zero significant parameter will be removed. Consequently, the non-implicitly issue did not solve by [23] except the empty column induced by similar objects is removable. Hence, the introduced hybrid algorithm in this study reduced the choices cost, which affects storage and transformation searching significantly. The similarity between the two algorithms is that it reduces non-implicitly in different strategy.

Some non-implicitly from finite parameters volume are shared by both algorithms from different aspects [14] and [23] that are induced by empty columns induced from [23]. However, in [14] the algorithm has automatic decompositions, based on singleton reduction for both choices cost and domain space reduction. Furthermore, the problem raise in both algorithms in terms of not singleton sub set. Thus, to overcome these problems, we proposed a hybrid algorithm to improve Kumar's, and Rose's algorithms.

A. HPC combination procedure:

The detailed procedure of the proposed HPC algorithm is explained as follows.

i. Filter parameters by Parameterization Reduction Using Soft Set Theory for Better Decision Making.
ii. Execute Hybrid reduction algorithm.

HPC Process:

i. Input soft set, which is two dimensional, parameters and objects (F,E).
ii. Determine parameters status in every object.
iii. Calculate the support of parameters co-occurrences based on step 2.
iv. Determine the partition of step 3 as U/E and determine minimum partition.
v. Begin with the first object check if there are objects maximally or minimally supported by E, then if the condition is satisfied, forward the object to set *D*. Repeat the process to check the status of the next object until the last object.
vi. From step 1, let c belongs to E then c is indispensable in *E*, if $U/\{c\}=U/E$.
vii. Let $C\subset E$ then C is indispensable in E, if all ci are indispensable, where C={c1,c2,c3,……..}. Then *C* is reduction if C is indispensable, otherwise, *C* is not considered for possible reduction.
viii. Repeat step 6 to determine the next c_i where i=1,2,……….|E|.
ix. The new soft set will be without *C*.
x. Let $A\subset E$ then A is indispensable in *E*, if $U/A=U/E$ otherwise A is dispensable in *E*.
xi. Set A is reduction in reduction in E if and only if A is dispensable and $\mathrm{supp}_{E\setminus A}(u)=\mathrm{supp}_{E\setminus A}(v)$, for every $u,v\in U$.
xii. The maximum cardinality is E-A-C-D.

V. PERFORMANCE EVALUATION

In this section the performance evaluation of our proposed HPC Algorithm has been discussed and analyzed in details. Moreover, a bench mark was conducted as a way to validate the performance of our proposed algorithm by fairly comparing it with other representatives in the field of normal parameter reduction in soft set. The following subsections are elaborating the performance evaluation for each stage of our proposed algorithm.

A. Decision Partition Order and Computational Cost

Optimal decision is an important business strategy that is determined with the best quality extension objective in reducing the overall cost under finite parameter. The minimum parameters were identified to fill the original decision partition completely in the reduction process, which became possible with the use of cluster and soft set in arranging the subsets as well as determining the spacing between rows supports. Small and large spacing of the support is determined based on a cluster that is relied on rough set equal classless (similarity) rather than on the rough set lower and upper approximations involved in the parameter reduction. In this section, the performance analysis of HPC algorithm is presented, which is followed by Framework Parameter reduction Combination (FPC), [14], [24]. Besides, the performance analysis of the alternative normal parameter reduction techniques has been discussed in this section.

Firstly, during the parameter reduction analysis, the original characteristic should be assigned to computational cost, but the question is, which characteristic should be assigned to a given boundary. Afterwards, the vagueness of some values inside the approximation range should be cleared during this analysis, which needs intelligent detections. To reduce the number of soft data, one can use set theory to analyse and simplify the huge data that help to set a unique original data characteristics. Several researchers have analysed the original decision partition situation; however, sometimes the problem encountered is that some amount of vagueness cannot be waived. To solve this problem, there is a need to study the characteristic of data and find their relations to determine the reduced data. Moreover, every soft reduction algorithm has to be assigned to decision partition and their order properties. The highest parameters reduction of independent decision partition order of original set verifications occurs at the maximum reduction, which is significantly closer to the original characteristics boundary gap based on cluster and soft set by our proposed HPC algorithm. Since the comparisons of any two decisions partitions state based on equal classes is circular, this proves the decision partition order. In filtering false parameters, there is no need to check the complete original objects support cluster, it is sufficient to check only the Min supp and, consequently, the false parameters can be differentiated. Then, Max supp is used to confirm the parameters that satisfy Min supp. Finally, R supp is used as a final check only to confirm those parameters that satisfy Min supp and Max supp clusters. The HPC algorithm is implemented in Java program as Net Beans IDE, 8.0.2 that is executed on Intel (R) Core (TM) 2 Duo CPU T6600@2.20 GZ running 32-bit operating system, Windows 7 with 3.00 GB RAM.

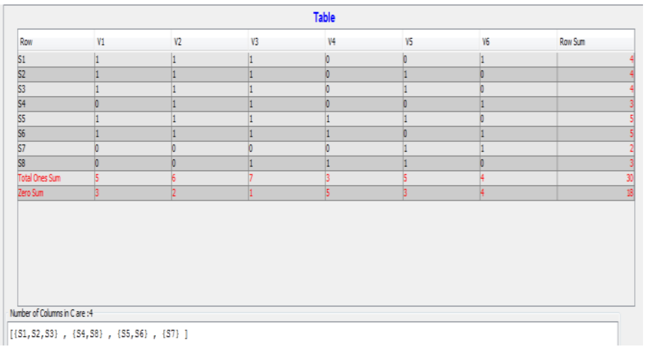
Since the reduction result is determined based on combinations, the problem that needs to be solved is how to reduce the number of combinations, rather than reducing the full subset combinations of elements. To search for the decision solutions, the sub-combination has to be validated by pre-processing the parameters, but an intelligent decision is required to identify where the solution is expected. However, the solution cannot be found if the computational boundary characteristic is not fitted well, causing unnecessary waste of time and producing wrong results. The various algorithms used in this study performed the candidate boundary computational tests in finding the minimum boundary to produce accurate decision results.

In Table 2, utilizing the representatives of normal parameter reduction algorithms, the measured soft parameter reductions are not able to perform any reduction results [24], [18], [23], [14], FPC and our HPC proposed algorithm. Figure 3 illustrates the pre-processes that were applied on the given soft set 2 using our developed java tool. We can observe the calculation for the number of availability/unavailability of parameter options represented by the total of 1’s and 0’s in each column and row. Moreover, we could view the generated categories of four ranked groups based on our proposed HPC algorithm.

On the other hand, we can observe clearly in Figure 4 that using only our proposed algorithm, the reduction was detected as {p3,p5 and p6}, in which they were deleted from the original set {p1,p2,p3,p4,p5,p6} as listed in Table 3, (after reduction). The parameter reduction efficiency for Table 2 is higher than several soft set reduction algorithms [24], [18], [23], [14], FPC, and our proposed HPC algorithm. The reason is that, for instance, the algorithm of Kumar and Rengasamy, (2013) has determined the reductions based on a single parameter, thus they employed this property to calculate the false parameters. However, when the parameters are deleted individually, the reduction cannot be represented in Table 2. Since implicit assumption condition did not occur in Table 2, even in case of applying rotation reduction, (rows reduction), no reduction has been produced when using the following algorithms [24], [18], [23], [14], FPC, and our proposed HPC algorithm.

Table 2
Tabular Representation of a Soft Set 2

U/P	p_1	p_2	p_3	p_4	p_5	p_6	$f(.)$
u_1	1	1	1	0	0	1	4
u_2	1	1	1	0	1	0	4
u_3	1	1	1	0	1	0	4
u_4	0	1	1	0	0	1	3
u_5	1	1	1	1	1	0	5
u_6	1	1	1	1	0	1	5
u_7	0	0	0	0	1	1	2
u_8	0	0	1	1	1	0	3



Table

Row	V1	V2	V3	V4	V5	V6	Row Sum
S1	1	1	1	0	0	1	4
S2	1	1	1	0	1	0	4
S3	1	1	1	0	1	0	4
S4	0	1	1	0	0	1	3
S5	1	1	1	1	1	0	5
S6	1	1	1	1	0	1	5
S7	0	0	0	0	1	1	2
S8	0	0	1	1	1	0	3
Total Ones Sum	5	6	7	3	5	4	30
Zero Sum	3	2	1	5	3	4	18

Number of Columns in C are :4

[{S1,S2,S3} , {S4,S8} , {S5,S6} , {S7}]

Figure 3: Analysis process on soft-set2 using our developed tool

With reference to Table 2, the results obtained from checking the soft set reduction based on the previous decompositions algorithms and our proposed algorithm are shown in Figure 4, in which it was noted that the dimension with fewer reductions is not minimized with algorithms [23]; [24]; [14], FPC, HPC. Utilizing our proposed HPC algorithm based on the hybrid model that was applied on soft set 2 in Table 2, the sub reduction has generated 20 spaces. It is found that the normal parameter reduction results at 20 spaces. On the other hand, elaborating the parameter reduction algorithms proposed by Ma et al., (2011) and Kumar and Rengasamy, (2013); they have checked 62, (2^n $n = number\ of\ parameters, 6$), combinations though the best reduction results could not be found. Therefore, we have considered the number of combinations that each algorithm needs to go through checking as a computational cost in finding the best normal parameter reduction. Since our proposed algorithm could find efficiently the solution within 20 spaces, the computational cost obtained is 20/64×100%=31.25%. As illustrated in Figure 5, the other algorithms failed in obtaining any reduction on soft set 2 in Table 2 after checking all the possible combinations 62, which means 100% computational cost.

Figure 6 presents the reduction percentage of the decision obtained using our proposed HPC algorithm compared with the state of the art. We can observe that we have achieved 40% of reduction compared with 37% using the proposed method by [23].

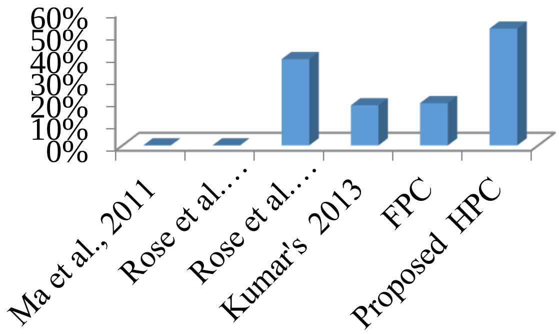


Figure 4: Represent reduction results of soft-set2

Table 3
Representation of Soft-Set2 In Table 2. After Reduction Using Our Proposed Algorithm

U/P	p_1	p_2	p_4	$f(.)$
u_1	1	1	0	2
u_2	1	1	0	2
u_3	1	1	0	2
u_4	0	1	0	1
u_5	1	1	1	3
u_6	1	1	1	3
u_7	0	0	0	0
u_8	0	0	1	1

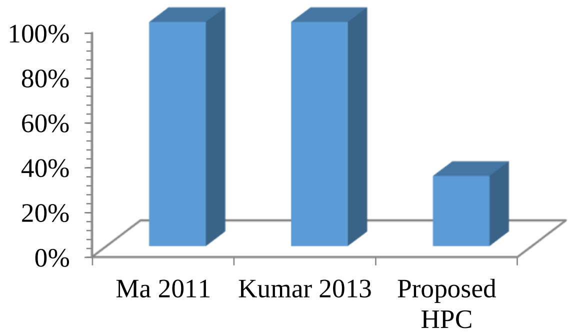


Figure 5: Computational cost based on soft-set2 in Table 2

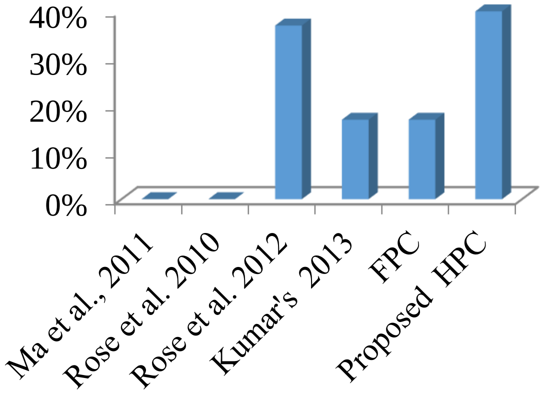


Figure 6: Reduction result of set 2.2

VI. CONCLUSION

This paper proposed hybrid parameter complement reduction algorithm, which is used for reducing the computational cost of search domain that could help in managing uncertain data and maintaining the consistency during parameter reduction process. The contribution of this study is to maintain consistency of optimal and sub optimal choices by the use of developed HPC algorithm. The enhancement in the achieved cost of parameter reduction has benefited the customers and decision/forecasting makers by utilising less data size, which is later used through transmission lines. The performance of the proposed HPC algorithm has solved the infinite machine state and improved the decision characteristics classifications by setting the decision partition and its order. The process of fixing original characteristics has produced minimized choice cost with high data quality, which has also simplified the decision representations. The reported results based on decision partition and its order has determined a new version of soft set reduction algorithm, which has uniquely addressed the issue of soft parameters reductions. On the other hand, the object or sub-set reduction has also been addressed in this paper. Finally, HPC algorithm has enhanced sub-set reduction by approximately 50% of improvement compared with [23]. In future studies, it would be interesting to investigate the efficiency of our proposed algorithm by implementing it into other research fields such as flood and disaster forecasting.

ACKNOWLEDGMENT

This work is funded by the University Malaysia Pahang research Grant – RDU1603129.

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