4.4. *Comparison of reduct classification rules with rough set and decision tree*

From the reduct obtained, rules are generated. From Table 6, it is clear that although the result for reduct is worst for decision tree technique but decision tree have the least rules generation for all datasets. There are some significant difference between DTSAR and rough set technique. Even though rough sets do outperformed DTSAR in generating reduct for the five datasets, the rule generated by one of the dataset is too huge until it reaches 2417 rules for lung dataset. DTSAR and rough set technique produce the same reduct for dataset exactly, exactly2 and m-of-n dataset as in Table 6, the rules generated by DTSAR are more than the rules generated by rough set. Overall, the rules generated by rough set are too many and is too complex to analyze if compared to DTSAR and decision tree. Figure 5 depicted the comparison of number of rules generated from reduct obtain from DTSAR and other techniques in graph.

Overall, among the three techniques, it can be summarized that DTSAR and rough set is comparable in term of the reduct obtained and the classification accuracy except for wq dataset, the rough set technique outperformed DTSAR in reduct very significantly.

5. Conclusion

This section summarized the works done in this research. The research is based on Tabu search approach towards attribute reduction using rough set theory. The approach introduced in this paper is the dynamic Tabu list and has been applied to the rough set attribute reduction. There are 13 well-known datasets being used in the research. In this research reducts obtained represent the data reduction for the dataset, the dimension of the dataset is reduced into smaller size. The results of the research show that dynamic Tabu list that is introduce to the Tabu search attribute reduction does give a promising result to the reduct.

The dynamic Tabu list is use to skip the aspiration criteria and to promote faster running times. However, the result obtained is comparable with previous research on Tabu search technique with static Tabu list. If the result is significant and better, it could be use to hybrid with other Metaheuristic for future attribute reduction purposes.

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