Chapter 5

Hybridization of PSO and IDS

5.1 Inroduction

This chapter further proposes two hybrid methods based on PSO and IDS. In the proposed hybrid methods an attempt has been made to use the complementary capabilities of PSO and IDS. The PSO algorithm is basically a swarm intelligence guided by its velocity term. The velocity is guiding term for a swarm in a general direction towards best solutions. The IDS is also a swarm intelligence technique which does not use any guiding term in its search rather it uses random movements which gives diversity. The hybridization approach adopted in this chapter is an attempt to take advantage of above characteristics offered by PSO and IDS. Results show that the proposed hybrid methods are robust and capable to compute the solution efficiently and quickly, maintaining the acceptable classification accuracy. PSO and IDS have been hybridized for simultaneous feature selection and the fitness function is computed using RS and FRS dependency measures. In the presented hybridization approach PSO and IDS are hybridized in such a way that population is shared between PSO and IDS. In the present work two approaches, namely "parallel" and "series" hybridization of PSO and IDS have been proposed and initialized for their performance.

As observed in earlier chapters to get the optimal or the best reduct for different dataset, several runs of the algorithm were done. In some of the run the candidate has achieved the best reduct, while in remaining runs the candidate has not achieve the best reduct, as it is apparent from the average value of reduct size and accuracy reported. To ensure that the search method applied gives best reduct it was needed that the diversity of search space be improved for achieving the best result in every run. Thereby ensuring the probability of best reduct. Parallelizing and serializing of algorithms was designed to achieve the diversity of search spaces. By doing so, the candidate has achieved the desired result i.e. getting the best reduct along with best dependency measure in almost every run.

Thus, the decision to parallelize or serialize the method is an informed one to achieve a certain goal. Thus the present approach is a hybrid approach and not an ensemble approach. The candidate agrees that there are several possibilities of ensemble and other methods proposed in the literature. However, the achieved best reduct would be the same. In the present thesis since the goal was achieved using proposed hybridization, the candidate has not investigated different possibilities of combining different methods.

Proposed parallel/serial approach is used to enhance the capability of a particular method, which may be a part of an ensemble. Whereas in ensemble methods, component algorithms are not hybridized, rather the output of the component algorithms are aggregated, in some way to achieve the better features.

5.2 PSO-IDS Hybrid Methods

5.2.1 Hybrid-P: Parallel PSO-IDS Hybrid Method

Figure 5.1 shows the scheme adopted while performing Parallel PSO-IDS hybrid (Hybrid-P) method. In this method, PSO and IDS are hybridized in such a way that in each iteration half of the population is processed through PSO and rest half of the population is processed through IDS in a parallel fashion. Both, PSO and IDS methods will have their own *gbests*, and the better one is considered as *gbest* of the whole population for the next iteration. This cycle is repeated till the termination criterion is met. The algorithm implementing Hybrid-P method is given in *Algorithm 6*.

5.2.2 Hybrid-S: Series PSO-IDS Hybrid Method

Figure 5.2 shows the scheme for Hybrid-S method. In this method hybridization of PSO and IDS is done in such a way that the whole population is first supplied to PSO for one iteration and then resulting population is supplied to IDS for the next iteration. The

Algorithm 6 Parallel Hybrid (Hybrid-P)

c_w, c_p, c_g, Positive constants between (0,1);
p_1, p_2, p_3, Probabilities between (0,1);
$Gbest_{pso}$, Gbest value provided by PSO part
$Gbest_{ids}$, Gbest value provided by IDS part
$P_{Gbest_{pso}}$, Global best solution provided by PSO part
$P_{Gbest_{ids}}$, Global best solution provided by IDS part
    /* DS-initialization begins */
For first one third solution $i = 1$ to $i/3$, initialize X_i
if $rand < p_1$ **then**
    $x_{i,j} = 0$;
else
    $x_{i,j} = 1$;
end if
For second one third solution $i = i/3 + 1$ to $2i/3$, initialize X_i
if $rand < p_2$ **then**
    $x_{i,j} = 0$;
else
    $x_{i,j} = 1$;
end if
For last one third solution $i = 2i/3 + 1$ to i, initialize X_i
if $rand < p_3$ **then**
    $x_{i,j} = 0$;
else
    $x_{i,j} = 1$;
end if
    /* DS-initialization ends */
while $K < MAXITER$ **do**
    $K = K + 1$;
    For every solution $i = 1$ to pop_size/2;
    Use Algorithm 1 for PSO for one iteration
    return $Gbest_{pso}$;
    For every solution i = pop_size/2 + 1 to i;
    Use Algorithm 3 for IDS for one iteration
    return $Gbest_{ids}$;
    if $Gbest_{pso} > Gbest_{ids}$ **then**
        $Gbest_{ids} = Gbest_{pso}$;
        return $P_{gbest_{pso}}$
    else if $Gbest_{ids} > Gbest_{pso}$ **then**
        $Gbest_{pso} = Gbest_{ids}$;
        $gbest_{pso} = gbest_{ids} + pop\_size/2$
        return $P_{gbest_{pso}}$
    end if
end while

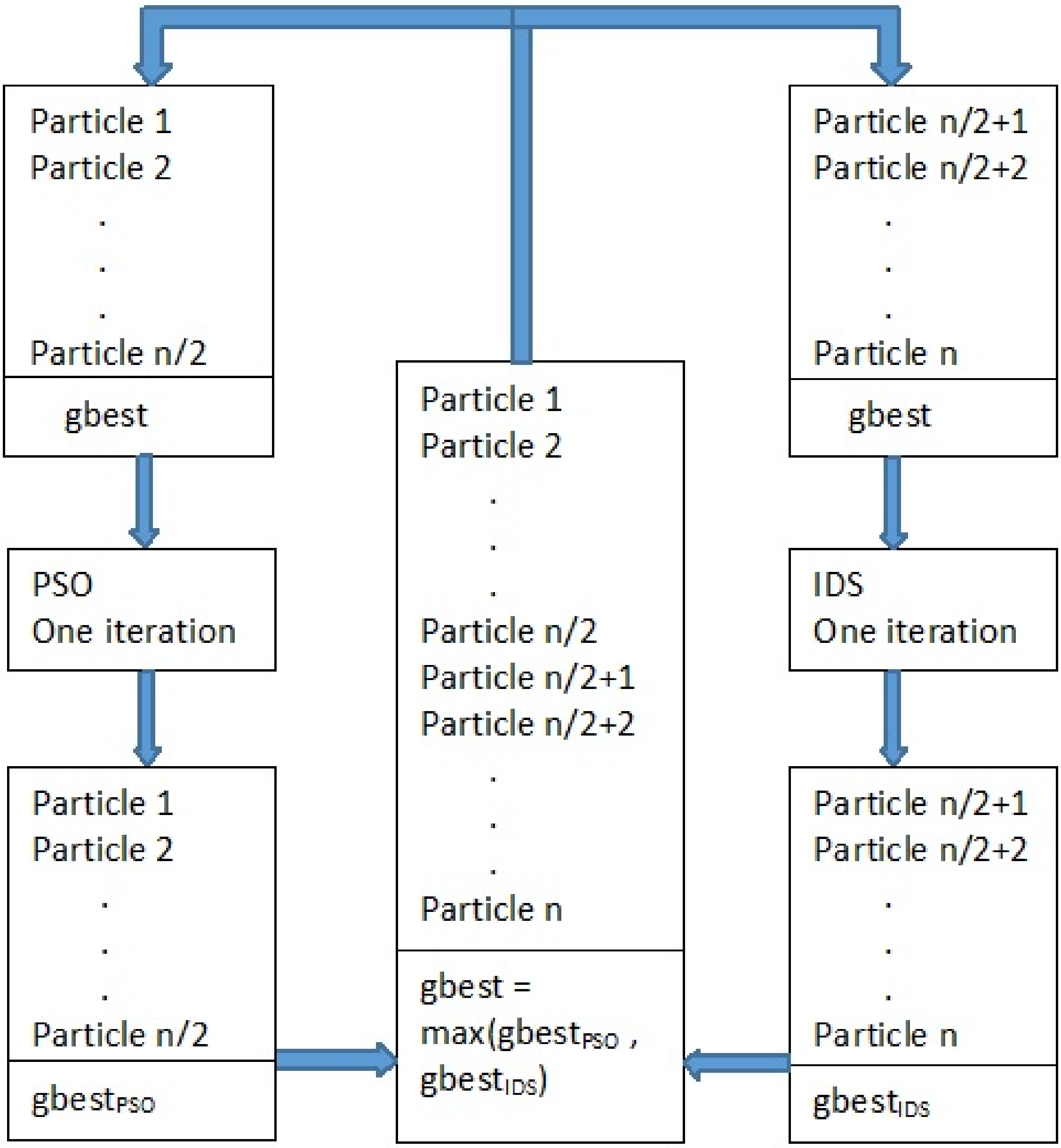

Figure 5.1: Parallel PSO-IDS hybrid method (Hybrid-P)

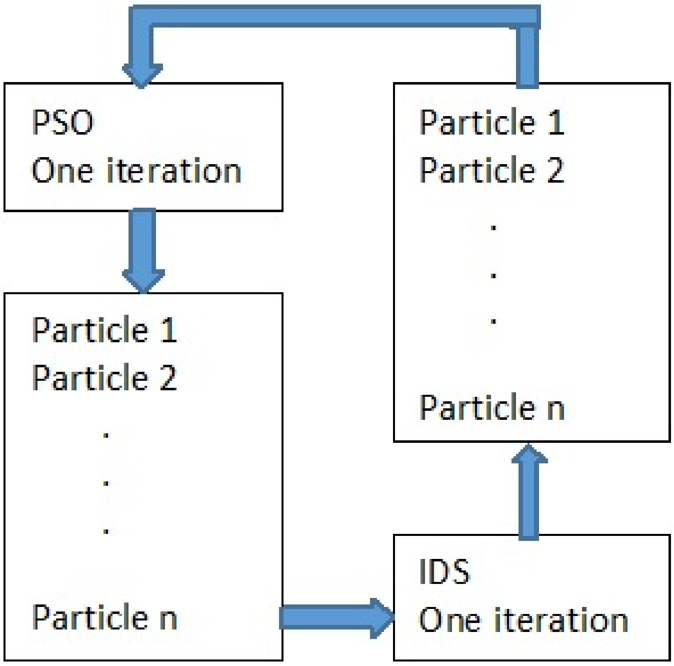

Figure 5.2: Series PSO-IDS hybrid method (Hybrid-S)

above cycle is repeated till the termination criterion is met. Thus this technique every generation consists of two generations one for PSO and one for IDS. Here we run the program with 50 generations each for PSO and IDS part. The algorithm implementing Hybrid-S method is given in *Algorithm 7*.

5.3 Results and Discussions

5.3.1 Hybrid methods with RST measure

In this work dataset and the experimental setup discussed in Section 4.3.1 have been used for evaluating the feature selection performance of hybrid method. Table 5.1 presents comparison of performance of proposed Hybrid-P method with PSO-DS and IDS-DS. Table 5.2 presents comparison of performance of proposed Hybrid-S method with PSO-DS and IDS-DS. From Table 5.1 and 5.2 it can be observed that, although in case of reasonably smaller datasets like *Cleveland, Ecoli, Glass* and *Wine* the Hybrid-P and Hybrid-S method do not have any special or significant impact in terms of reduct size over PSO-DS and IDS-DS, they certainly improve the classification accuracy in most of

Algorithm 7 Series Hybrid (Hybrid-S)

c_w, c_p, c_g, Positive constants between (0,1);

p_1, p_2, p_3, Probabilities between (0,1);

$Gbest_{pso}$, Gbest value provided by PSO part

$Gbest_{ids}$, Gbest value provided by IDS part

$P_{Gbest_{pso}}$, Global best solution provided by PSO part

$P_{Gbest_{ids}}$, Global best solution provided by IDS part

/* DS-initialization begins */

For first one third solution $i = 1$ to $i/3$, initialize X_i

if $rand < p_1$ **then**

$x_{i,j} = 0$;

else

$x_{i,j} = 1$;

end if

For second one third solution $i = i/3 + 1$ to $2i/3$, initialize X_i

if $rand < p_2$ **then**

$x_{i,j} = 0$;

else

$x_{i,j} = 1$;

end if

For last one third solution $i = 2i/3 + 1$ to i, initialize X_i

if $rand < p_3$ **then**

$x_{i,j} = 0$;

else

$x_{i,j} = 1$;

end if

/* DS-initialization ends */

while $K < MAXITER$ **do**

$K = K + 1$;

For every solution i;

Use Algorithm 1 for PSO for one iteration

return $Gbest_{pso}$, $P_{gbest_{pso}}$;

For every solution i;

Use Algorithm 3 for IDS for one iteration

return $Gbest_{ids}$, $P_{gbest_{ids}}$;

if $Gbest_{pso} > Gbest_{ids}$ **then**

$Gbest_{ids} = Gbest_{pso}$;

return $P_{gbest_{pso}}$

else if $Gbest_{ids} > Gbest_{pso}$ **then**

$Gbest_{pso} = Gbest_{ids}$;

return $P_{gbest_{ids}}$

end if

end while

the cases due to different combination of features resulting as a reduct.

Table 5.1: Hybrid-P with RST measure: Comparison of reduct size and classification accuracy with statistical t-test, and Wilcoxon test. [Classification accuracy is denoted as 'CA'. Statistical t-test is denoted as 'S'. Wilcoxon test is denoted as 'WT'. Mean Subset Size is denoted as 'MSS'.]

Dataset (Total features)	Feature Selection Method	Feature Subset Size				Classification Accuracy (CA)												Best result reported in literature	
						Classifier : J48				Classifier : JRip				Classifier : PART					
		Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	MSS	CA
	PSO-DS	3	3(0)	-	-	55.44	51.92(2.85)	-	-	53.46	52.82(0.328)	-	-	54.78	52(2.652)	-	-		
Cleveland(13)	IDS-DS	3	3(0)	-	-	55.44	52.69(1.581)	-	-	**56.1**	53.62(1.538)	*	*	54.78	51.39(2.092)	-	-	7.81 [30]	52.6 [30]
	Hybrid-P	**3**	3(0)			55.44	51.61(2.406)			53.46	52.66(0.432)			54.78	51.28(2.652)				
	PSO-DS	3	3(0)	-	-	79.46	76.47(3.25)	-	-	80.95	75.32(4.44)	-	-	80.95	75.59(4.55)	-	-		
Ecoli(7)	IDS-DS	3	3(0)	-	-	79.46	77.13(2.46)	-	-	80.95	76.24(3.78)	-	-	80.95	76.34(3.52)	-	-	3 [52]	77.38 [52]
	Hybrid-P	**3**	3(0)			79.46	76.8(3.5)			**80.95**	76.33(4.98)			80.95	76.8(5.2)				
	PSO-DS	2	2(0)	-	-	66.36	56.81(7.07)	-	-	64.95	55.96(8.23)	-	-	68.22	57.43(8.7)	-	-		
Glass(9)	IDS-DS	2	2(0)	-	-	66.36	60.51(5.31)	-	-	63.08	57.91(5.36)	-	-	68.22	59.58(6.07)	-	-	8.44 [30]	65.14 [30]
	Hybrid-P	**2**	2(0)			66.36	60.39(5.36)			64.95	59.38(6.3)			**68.22**	59.89(6.47)				
	PSO-DS	2	2.67(0.49)	-	-	89.74	83.9(2.89)	v	v	89.17	85.47(2.68)	-	-	88.89	82.69(2.87)	v	v		
Ionosphere(34)	IDS-DS	2	3(0.43)	v	v	88.89	84.83(2.62)	-	-	88.89	84.71(2.3)	-	-	90.31	84.05(3.18)	-	-	7.3 [30]	86.17 [30]
	Hybrid-P	**2**	**2.58(0.515)**			**90.31**	86.2(2.36)			89.46	86.51(2.02)			89.17	85.78(2.36)				
	PSO-DS	**3**	**5(1.04)**	-	-	**87.5**	77.08(8.25)	-	-	87.5	76.03(8.671)	-	-	84.37	75.51(8.922)	-	-		
Lung(56)	IDS-DS	5	5.92(0.67)	v	v	87.5	69(8.983)	-	-	87.5	69.78(8.463)	-	-	84.37	69.26(9.685)	-	-	NA	NA
	Hybrid-P	4	4.67(0.49)			84.37	71.35(8.085)			84.37	72.65(5.976)			81.25	70.31(6.321)				
Soybean	PSO-DS	2	2.16(0.39)	-	-	100	99.29(2.13)	-	-	100	99.29(2.93)	-	-	100	99.29(2.13)	-	-		
small(35)	IDS-DS	2	2.75(0.87)	v	v	100	98.94(2.13)	-	-	100	98.22(3.25)	-	-	100	99.11(2.12)	-	-	2 [29]	100 [29]
	Hybrid-P	**2**	**2(0)**			**100**	100(0)			100	100(0)			100	100(0)				
	PSO-DS	2	2(0)	-	-	94.94	81.46(11.1)	-	-	90.45	80.52(10.09)	-	-	93.82	81.27(10.77)	-	-		
Wine(13)	IDS-DS	2	2(0)	-	-	**94.94**	76.69(8.32)	-	-	90.45	75.23(7.12)	v	v	93.26	76.78(8.39)	-	-	2 [52]	90.44 [52]
	Hybrid-P	**2**	2(0)			84.83	81.6(2.85)			83.71	80.945(3.02)			85.39	80.95(3.58)				
	PSO-DS	14	17.75(1.86)	v	v	79.37	75.26(3.66)	-	-	84.92	75.6(4.3)	-	-	80.16	75.4(3.68)	-	-		
LSVT(310)	IDS-DS	18	20.67(2.1)	v	v	84.13	75.4(4.69)	-	-	80.95	75.13(3.83)	-	-	79.37	73.74(4.59)	-	-	NA	NA
	Hybrid-P	**3**	**8.58(3.11)**			**84.92**	76.19(4.59)			84.92	76.52(4.51)			80.95	76.32(4.04)				

Table 5.2: Hybrid-S with RST measure: Comparison of reduct size and classification accuracy with statistical t-test, and Wilcoxon test. [Classification accuracy is denoted as 'CA'. Statistical t-test is denoted as 'S'. Wilcoxon test is denoted as 'WT'. Mean Subset Size is denoted as 'MSS'.]

Dataset (Total features)	Feature Selection Method	Feature Subset Size				Classification Accuracy (CA)												Best result reported in literature	
						Classifier : J48				Classifier : JRip				Classifier : PART					
		Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	MSS	CA
Cleveland(13)	PSO-DS	3	3(0)	-	-	55.44	51.92(2.85)	-	-	53.46	52.82(0.328)	-	-	54.78	52(2.652)	-	-	7.81 [30]	52.6 [30]
	IDS-DS	3	3(0)	-	-	55.44	52.69(1.581)	-	-	**56.1**	53.62(1.538)	-	-	54.78	51.39(2.092)	-	-		
	Hybrid-S	**3**	3(0)			55.44	51.81(3.365)			53.46	52.99(0.432)			54.78	50.84(2.892)				
Ecoli(7)	PSO-DS	3	3(0)	-	-	79.46	76.47(3.25)	-	-	80.95	75.32(4.44)	-	-	80.95	75.59(4.55)	-	-	3 [52]	77.38 [52]
	IDS-DS	3	3(0)	-	-	79.46	77.13(2.46)	-	-	80.95	76.24(3.78)	-	-	80.95	76.34(3.52)	-	-		
	Hybrid-S	**3**	3(0)			79.46	75.17(4.13)			**80.95**	73.51(5.1)			80.95	73.86(5.65)				
Glass(9)	PSO-DS	2	2(0)	-	-	66.36	56.81(7.07)	v	v	64.95	55.96(8.23)	-	-	68.22	57.43(8.7)	v	v	8.44 [30]	65.14 [30]
	IDS-DS	2	2(0)	-	-	66.36	60.51(5.31)	-	-	63.08	57.91(5.36)	-	-	68.22	59.58(6.07)	-	-		
	Hybrid-S	**2**	2(0)			66.36	61.68(3.81)			64.95	59.15(3.87)			**68.22**	60.75(5.05)				
Ionosphere(34)	PSO-DS	2	2.67(0.49)	v	v	89.74	83.9(2.89)	-	-	89.17	85.47(2.68)	-	-	88.89	82.69(2.87)	-	-	7.3 [30]	86.17 [30]
	IDS-DS	2	3(0.43)	v	v	88.89	84.83(2.62)	-	-	88.89	84.71(2.3)	-	-	**90.31**	84.05(3.18)	-	-		
	Hybrid-S	**2**	**2.25(0.45)**			88.89	84.95(2.16)			88.32	85.23(1.32)			87.75	83.99(2.09)				
Lung(56)	PSO-DS	3	5(1.04)	-	-	87.5	77.08(8.25)	-	-	87.5	76.03(8.671)	-	-	84.37	75.51(8.922)	-	-	NA	NA
	IDS-DS	5	5.92(0.67)	v	v	87.5	69(8.983)	-	-	87.5	69.78(8.463)	-	-	84.37	69.26(9.685)	-	-		
	Hybrid-S	**3**	**4.58(0.668)**			**87.5**	76.82(10.86)			87.5	75.25(9.37)			87.5	76.3(8.37)				
Soybean small(35)	PSO-DS	**2**	**2.16(0.39)**	-	-	**100**	99.29(2.13)	-	-	100	99.29(2.93)	-	-	100	99.29(2.13)	-	-	2 [29]	100 [29]
	IDS-DS	2	2.75(0.87)	v	v	100	98.94(2.13)	-	-	100	98.22(3.25)	-	-	100	99.11(2.12)	-	-		
	Hybrid-S	2	2(0)			100	100(0)			100	100(0)			100	100(0)				
Wine(13)	PSO-DS	2	2(0)	-	-	94.94	81.46(11.1)	-	-	90.45	80.52(10.09)	-	-	93.82	81.27(10.77)	-	-	2 [52]	90.44 [52]
	IDS-DS	2	2(0)	-	-	**94.94**	76.69(8.32)	-	-	90.45	75.23(7.12)	-	-	93.26	76.78(8.39)	-	-		
	Hybrid-S	**2**	2(0)			93.82	79.78(8.36)			90.45	77.8(7.003)			93.82	79.59(8.64)				
LSVT(310)	PSO-DS	14	17.75(1.86)	v	v	79.37	75.26(3.66)	-	-	**84.92**	75.6(4.3)	-	-	80.16	75.4(3.68)	-	-	NA	NA
	IDS-DS	18	20.67(2.1)	v	v	84.13	75.4(4.69)	-	-	80.95	75.13(3.83)	-	-	79.37	73.74(4.59)	-	-		
	Hybrid-S	**12**	**14.75(2.3)**			84.13	75.46(3.67)			80.16	74.47(3.46)			80.16	74.14(3.75)				

Table 5.3: Friedman ranking with RST measure

Methods	FR	Rank
Hybrid-P	2.4688	1
Hybrid-S	3.1719	2
PSO-DS	3.5469	3
PSO-RANDOM	3.8125	4
IDS-DS	3.9688	5
IDS-RANDOM	4.0313	6

It is also observed from the tables that in case of *Ionosphere* dataset, Hybrid-P and Hybrid-S improve the average number of selected features and classification accuracy. Further, results on the datasets having relatively large number of features (*Lung, Soybean-small* and *LSVT*) demonstrate the power of proposed methods because these methods improve classification accuracy with smaller reduct size, for example in *Lung, Soybean-small* and *LSVT* datasets.

In the case of *Lung* dataset, both the proposed hybrid methods yield reduct size less than 5. Both the hybrid methods, have either improved or equivalent classification accuracy as compared to other method used in this chapter.

In the case of *Soybean-small*, it is observed that both the proposed hybrid methods provide the consistent results in every run. Thus, it yields smallest reduct size in all its run.

In the case of *LSVT*, proposed Hybrid-P method provides the best results in terms of selected features. Here the minimum number of selected features are only 3 out of 310 and the average number of a selected feature are less than 9, without compromising the classification accuracy. Proposed Hybrid-S method yields minimum and average number of selected features as 12 and 14.75 respectively (Tables 5.1 and 5.2). The 3 selected features (namely feature numbers 68,200,268) are the features having more classification accuracy compared to that of the 12 selected features (namely feature numbers 3,8,59,111,126,154,165,181,214,224,228,231) out of total 310 features.

For different runs, reducts may be obtained with same fitness value, for example in the case of *Wine* dataset, though s.d. of reduct size is zero but s.d. of classification accuracy is not. Bacause the combination of reducts are not the same. Improved values of classification accuracy and fitness measures are clearly demonstrated by both of the proposed methods.

All above results tabulated in Tables 5.1 and 5.2 are validated with the statistical parametric test, t-test (denoted 'S') and non parametric test, Wilcoxon test (denoted 'WT'). Further, Friedman ranking is also performed for feature selection methods, as shown in Table 5.3. Table 5.3 suggests that proposed Hybrid-P and Hybrid-S methods are superior to DS initialized or randomly initialized PSO and IDS methods.

Tables 5.1 and 5.2 show best results reported in literature in terms of Mean Subset size (denoted as MSS) and classification accuracy (denoted as CA). Further, it is evident from the Tables 1.1, 5.1 and 5.2 that the performance of Hybrid-P and Hybrid-S is better than that of state-of-the-art methods suggested in literature. While using rough dependency measure as fitness function, these method provides smaller reduct with comparable or more accuracy than the existing best method reported in literature, for all the dataset.

Both the proposed methods show that they are comparable to each other in terms of number of features selected and fitness values. Especially in $LSVT$ dataset the proposed methods of feature selection drastically reduces the selected number of features and execution time. This shows the improved power and robustness of proposed methods for high dimensional dataset.

5.3.2 Hybrid methods with L-FRFS measure

In this work dataset represented in Section 4.3.1, and the experimental setup discussed in Section 4.4.1 have been used for evaluating the feature selection performance of hybrid method. Table 5.4 presents a comparison of the performance of proposed Hybrid-P method with PSO-DS and IDS-DS. Table 5.5 presents comparison of performance of proposed Hybrid-S method with PSO-DS and IDS-DS. From Table 5.4 and 5.5 it can be observed that, although in case of reasonably smaller datasets like *Cleveland, Ecoli, Glass* and *Wine* the Hybrid-P and Hybrid-S method do not have any special or significant impact in terms of reduct size over PSO-DS and IDS-DS, they certainly improve the classification accuracy in most of the cases due to different combination of features resulting as a reduct.

It is also observed from the tables that in case of *Ionosphere* dataset, Hybrid-P and

Hybrid-S improve the average number of selected features and classification accuracy. Further, results on the datasets having relatively large number of features (*Lung, Soybean-small* and $LSVT$) demonstrate the power of proposed methods because these methods improve classification accuracy with smaller reduct size, for example in *Lung, Soybean-small* and $LSVT$ datasets.

Table 5.4: Hybrid-P with L-FRFS measure: Comparison of reduct size and classification accuracy with statistical t-test, and Wilcoxon test. [Classification accuracy is denoted as 'CA'. Statistical t-test is denoted as 'S'. Wilcoxon test is denoted as 'WT'. Mean Subset Size is denoted as 'MSS'.]

Dataset (Total features)	Feature Selection Method	Subset Size				Classification Accuracy (CA)												Best result reported in literature	
						Classifier : J48				Classifier : JRip				Classifier : PART					
		Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	MSS	CA
Cleveland(13)	PSO-DS	6	6(0)	-	-	52.47	52.47(0)	-	-	53.79	53.79(0)	-	-	52.14	52.14(0)	-	-	7.81 [30]	52.6 [30]
	IDS-DS	6	6.41(0.51)	v	v	52.47	51.81(0.82)	v	v	53.79	53.54(0.31)	v	v	52.14	50.4(2.39)	v	v		
	Hybrid-P	**6**	**6(0)**			52.47	52.47(0)			**53.79**	53.79(0)			52.14	52.14(0)				
Ecoli(7)	PSO-DS	5	5(0)	-	-	82.44	82.44(0)	-	-	81.25	81.25(0)	-	-	80.65	80.65(0)	-	-	3 [52]	77.38 [52]
	IDS-DS	5	5(0)	-	-	82.44	82.44(0)	-	-	81.25	81.25(0)	-	-	80.65	80.65(0)	-	-		
	Hybrid-P	**5**	5(0)			**82.44**	82.44(0)			81.25	81.25(0)			80.65	80.65(0)				
Glass(9)	PSO-DS	8	8(0)	-	-	64.49	64.49(0)	-	-	69.16	69.16(0)	-	-	68.69	68.69(0)	-	-	8.44 [30]	65.14 [30]
	IDS-DS	8	8(0)	-	-	64.49	64.49(0)	-	-	69.16	69.16(0)	-	-	68.69	68.69(0)	-	-		
	Hybrid-P	**8**	8(0)			64.49	64.49(0)			**69.16**	69.16(0)			68.69	68.69(0)				
Ionosphere(34)	PSO-DS	6	7(0.6)	v	v	91.74	89.58(1.73)	-	-	91.74	89.07(1.79)	-	-	91.7	89.52(1.52)	-	-	7.3 [30]	86.17 [30]
	IDS-DS	7	7.83(0.57)	v	v	93.73	89.86(2.15)	-	-	92.02	89.31(1.82)	-	-	93.73	89.05(2.39)	-	-		
	Hybrid-P	**6**	**6.16(0.38)**			93.45	90.45(1.92)			91.45	89.29(1.52)			93.45	90.17(1.89)				
Lung(56)	PSO-DS	4	4.91(0.79)	-	-	87.5	74.21(7.78)	-	-	87.5	76.29(7.1)	-	-	87.5	75.25(7.93)	-	-	NA	NA
	IDS-DS	5	6.25(0.62)	v	v	87.5	78.12(7.17)	-	-	87.5	75.25(10.94)	-	-	87.5	74.73(8.04)	-	-		
	Hybrid-P	**3**	**4.33(0.65)**			84.37	72.39(8.08)			**87.5**	73.69(8.47)			81.25	71.61(6.17)				
Soybean small(35)	PSO-DS	2	2.25(0.45)	-	-	100	99.64(0.82)	-	-	100	99.64(0.82)	-	-	100	99.64(0.82)	-	-	2 [29]	100 [29]
	IDS-DS	2	2.75(0.62)	v	v	100	99.29(1.38)	-	-	100	99.64(0.82)	-	-	100	99.64(0.82)	-	-		
	Hybrid-P	**2**	**2(0)**			**100**	100(0)			100	100(0)			100	100(0)				
Wine(13)	PSO-DS	4	4(0)	-	-	93.82	93.07(0.8)	v	v	92.13	90.91(1.08)	*	*	93.82	92.78(1.14)	v	v	2 [52]	90.44 [52]
	IDS-DS	4	4(0)	-	-	93.82	93.54(0.5)	-	-	91.57	90.31(0.75)	-	-	93.82	93.11(1.27)	-	-		
	Hybrid-P	**4**	4(0)			**93.82**	93.67(0.48)			92.13	90.07(0.64)			93.82	93.67(0.48)				
LSVT(310)	PSO-DS	13	16.5(2.11)	v	v	**82.54**	73.14(5.12)	-	-	80.95	74.2(3.93)	-	-	80.95	73.41(5.51)	-	-	NA	NA
	IDS-DS	16	20.75(2.86)	v	v	80.95	75.52(4.19)	-	-	83.33	75.13(3.84)	-	-	78.57	72.61(3.75)	-	-		
	Hybrid-P	**8**	**11.16(1.94)**			81.75	75.6(3.76)			80.16	76.42(3.7)			80.16	75.33(3.79)				

Table 5.5: Hybrid-S with L-FRFS measure: Comparison of reduct size and classification accuracy with statistical t-test, and Wilcoxon test. [Classification accuracy is denoted as 'CA'. Statistical t-test is denoted as 'S'. Wilcoxon test is denoted as 'WT'. Mean Subset Size is denoted as 'MSS'.]

Dataset (Total features)	Feature Selection Method	Subset Size				Classification Accuracy (CA)												Best result reported in literature	
						Classifier : J48				Classifier : JRip				Classifier : PART					
		Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	Best	Mean(s.d.)	S	WT	MSS	CA
Cleveland(13)	PSO-DS	6	6(0)	-	-	52.47	52.47(0)	-	-	53.79	53.79(0)	-	-	52.14	52.14(0)	-	-	7.81 [30]	52.6 [30]
	IDS-DS	6	6.41(0.51)	v	v	52.47	51.81(0.82)	v	v	53.79	53.54(0.31)	v	v	52.14	50.4(2.39)	v	v		
	Hybrid-S	**6**	**6(0)**			52.47	52.47(0)			**53.79**	53.79(0)			52.14	52.14(0)				
Ecoli(7)	PSO-DS	5	5(0)	-	-	82.44	82.44(0)	-	-	81.25	81.25(0)	-	-	80.65	80.65(0)	-	-	3 [52]	77.38 [52]
	IDS-DS	5	5(0)	-	-	82.44	82.44(0)	-	-	81.25	81.25(0)	-	-	80.65	80.65(0)	-	-		
	Hybrid-S	**5**	5(0)			**82.44**	82.44(0)			81.25	81.25(0)			80.65	80.65(0)				
Glass(9)	PSO-DS	8	8(0)	-	-	64.49	64.49(0)	-	-	69.16	69.16(0)	-	-	68.69	68.69(0)	-	-	8.44 [30]	65.14 [30]
	IDS-DS	8	8(0)	-	-	64.49	64.49(0)	-	-	69.16	69.16(0)	-	-	68.69	68.69(0)	-	-		
	Hybrid-S	**8**	8(0)			64.49	64.49(0)			**69.16**	69.16(0)			68.69	68.69(0)				
Ionosphere(34)	PSO-DS	6	7(0.6)	v	v	91.74	89.58(1.73)	-	-	91.74	89.07(1.79)	-	-	91.7	89.52(1.52)	-	-	7.3 [30]	86.17 [30]
	IDS-DS	7	7.83(0.57)	v	v	**93.73**	89.86(2.15)	-	-	92.02	89.31(1.82)	-	-	93.73	89.05(2.39)	-	-		
	Hybrid-S	**6**	**6.08(0.28)**			90.88	89.52(0.84)			91.74	89.38(1.27)			91.74	89.14(1.07)				
Lung(56)	PSO-DS	4	4.91(0.79)	-	-	87.5	74.21(7.78)	-	-	87.5	76.29(7.1)	-	-	87.5	75.25(7.93)	-	-	NA	NA
	IDS-DS	5	6.25(0.62)	v	v	87.5	78.12(7.17)	-	-	87.5	75.25(10.94)	-	-	87.5	74.73(8.04)	-	-		
	Hybrid-S	**3**	**4.5(0.79)**			**87.5**	79.42(8.88)			87.5	79.16(8.25)			87.5	74.73(9.65)				
Soybean small(35)	PSO-DS	2	2.25(0.45)	-	-	100	99.64(0.82)	-	-	100	99.64(0.82)	-	-	100	99.64(0.82)	-	-	2 [29]	100 [29]
	IDS-DS	2	2.75(0.62)	v	v	100	99.29(1.38)	-	-	100	99.64(0.82)	-	-	100	99.64(0.82)	-	-		
	Hybrid-S	**2**	**2(0)**			**100**	100(0)			100	100(0)			100	100(0)				
Wine(13)	PSO-DS	**4**	4(0)	-	-	93.82	93.07(0.8)	v	v	92.13	90.91(1.08)	*	*	93.82	92.78(1.14)	v	v	2 [52]	90.44 [52]
	IDS-DS	4	4(0)	-	-	93.82	93.54(0.5)	-	-	91.57	90.31(0.75)	-	-	93.82	93.11(1.27)	-	-		
	Hybrid-S	4	4(0)			**93.82**	93.82(0)			89.89	89.89(0)			93.82	93.82(0)				
LSVT(310)	PSO-DS	13	16.5(2.11)	v	v	82.54	73.14(5.12)	-	-	80.95	74.2(3.93)	-	-	80.95	73.41(5.51)	-	-		
	IDS-DS	16	20.75(2.86)	v	v	80.95	75.52(4.19)	-	-	83.33	75.13(3.84)	-	-	78.57	72.61(3.75)	-	- NA		NA
	Hybrid-S	**9**	**14.75(2.09)**			83.33	75.26(6.67)			81.75	76.52(4.23)			**84.13**	75.59(6.45)				

In the case of *Lung* dataset, both the proposed hybrid methods yield reduct size less than 5. Both the hybrid methods, have either improved or equivalent classification accuracy as compared to other method used in this chapter.

In the case of *Soybean-small*, it is observed that both the proposed hybrid methods provide the consistent results in every run. Thus, it yields smallest reduct size in all its run.

In the case of *LSVT*, proposed Hybrid-P method provides the best results in terms of selected features. Proposed Hybrid-P method yields minimum and average number of selected features as 8 and 11.16 respectively, proposed Hybrid-S method yields minimum and average number of selected features as 9 and 14.75 respectively (Tables 5.4 and 5.5) without compromising the classification accuracy.

All above results tabulated in Tables 5.4 and 5.5 are validated with statistical parametric test, t-test (denoted 'S') and non parametric test, Wilcoxon test (denoted 'WT'). Further, Friedman ranking is also performed for feature selection methods, as shown in Table 5.6. Table 5.6 suggests that proposed Hybrid-P and Hybrid-S methods are superior to DS initialized or randomly initialized PSO and IDS methods.

Tables 5.4 and 5.5 show best results reported in literature in terms of Mean Subset size (denoted as MSS) and classification accuracy (denoted as CA). Further, it is evident from the Tables 1.1, 5.4 and 5.5 that the performance of Hybrid-P and Hybrid-S is better than that of state-of-the-art methods suggested in literature for the dataset *Cleveland*, *Glass* and *Ionosphere*. While using fuzzy rough dependency measure as fitness function, these method provides better accuracy for *Ecoli* and *Wine* dataset at the cost of relatively large reduct size than the existing best method reported in literature.

Both the proposed methods show that they are comparable to each other in terms of the number of features selected and fitness values. Especially in *LSVT* dataset the proposed methods of feature selection drastically reduces the selected number of features and execution time. This shows the improved power and robustness of proposed methods for high dimensional dataset.

Table 5.6: Friedman ranking with L-FRFS measure

Methods	FR	Rank
Hybrid-S	2.5781	1
Hybrid-P	2.6406	2
PSO-DS	3.3438	3
IDS-DS	3.8906	4
PSO-RANDOM	3.9844	5
IDS-RANDOM	4.5625	6

5.4 Conclusion

New feature selection methods viz. Hybrid-P and Hybrid-S have been proposed in this chapter. The methods use RST and L-FRFS measures as their fitness measures. These methods were developed employing hybridization of PSO and IDS to take the advantage of random exploration of IDS and guided search of PSO. These two hybrid methods were tested for different datasets and the effectiveness of the methods was established in terms of reducts achieved. The proposed methods have shown their effectiveness on large and practical datasets where feature selection are relevant and significant. Proposed Hybrid-P and Hybrid-S methods used DS-initialization. Effect of hybrid methods in terms of classification accuracy is not only visible in smaller dataset but also in reasonably large sized dataset as well. It is observed that in most of the datasets Hybrid-P method performs better than Hybrid-S method. However, in certain datasets the performance of Hybrid-S method was found better. Hence both the proposed methods should be attempted for a given dataset.

It is also observed from the Friedman ranking test, that with RST measure, rank of Hybrid-P method is better than that of Hybrid-S, but with L-FRFS measure, rank of Hybrid-S method is better than that of Hybrid-P. Other methods namely PSO-DS and IDS-DS preserves their ranking order of performance, regardless of fitness measure (RST or L-FRFS) used.