

It is worth to mention that the comparison of the results (Table A.1) aims to show that the usage of proposed AIC gives the satisfactory results in terms of system accuracy. Using more sophisticated or more complex computational intelligence systems can get better results in terms of accuracy, however, these approaches do not take into account the interpretability of the systems and low complexity.

Table A.1: Comparison of obtained error of the systems with results of the other authors.

problem	method	best		avg	
		RMSE	$err(\cdot)$	RMSE	$err(\cdot)$
BJGF	proposed, $int(\cdot) < 0.1$	0.3755	0.0185	0.5775	0.0290
	proposed, $int(\cdot) < 0.2$	0.3308	0.0161	0.4828	0.0242
	proposed, $int(\cdot) < 0.4$	0.3084	0.0146	0.4210	0.0200
	Box & Jenkins [2]	-	-	0.4494	-
	GPFS [4]	0.4010	-	0.4320	0.0190
	GPFS [6]	0.3633	-	0.4120	-
CHPL	proposed, $int(\cdot) < 0.1$	0.0059	0.0066	0.0121	0.0139
	proposed, $int(\cdot) < 0.2$	0.0055	0.0058	0.0102	0.0117
	proposed, $int(\cdot) < 0.4$	0.0055	0.0058	0.0085	0.0098
	GPFS [6]	0.0065	-	0.0081	-
	EFS+BL [5]	0.0117	-	0.0379	-
	S3+OP [7]	-	-	-	0.0104
	Pal & Chakraborty [9]	-	-	0.0092	-
HANG	proposed, $int(\cdot) < 0.1$	0.1189	0.0260	0.2474	0.0485
	proposed, $int(\cdot) < 0.2$	0.0975	0.0203	0.2084	0.0407
	proposed, $int(\cdot) < 0.4$	0.0870	0.0196	0.1753	0.0362
	GPFS [4]	0.0780	-	0.1370	0.0370
	EFS+BL [5]	0.1153	-	0.3040	-
SDAP	proposed, $int(\cdot) < 0.1$	379.37	0.0954	446.61	0.1093
	proposed, $int(\cdot) < 0.2$	368.50	0.0915	438.70	0.1076
	proposed, $int(\cdot) < 0.4$	361.24	0.0899	434.74	0.1067
SLCN	proposed, $int(\cdot) < 0.1$	3.7372	0.0362	7.5244	0.0800
	proposed, $int(\cdot) < 0.2$	3.0840	0.0295	6.6562	0.0718
	proposed, $int(\cdot) < 0.4$	2.3812	0.0226	6.1684	0.0672
	M-RLSR [1]	-	-	6.3640	-
	KP [8]	-	-	6.2870	0.0612
	S3+OP [7]	-	-	-	0.0624
	KNN [10]	-	-	8.2800	-
	SVM [10]	-	-	6.5190	-
RBR [10]	-	-	3.6500	-	
YAHD	proposed, $int(\cdot) < 0.1$	1.6539	0.0163	6.0157	0.0689
	proposed, $int(\cdot) < 0.2$	1.4167	0.0158	4.9007	0.0560
	proposed, $int(\cdot) < 0.4$	1.1733	0.0115	4.0242	0.0458
	M-RLSR [1]	-	-	9.9872	-
	TNFS [3]	-	-	2.6140	0.0270
	GPFS [4]	0.6900	-	1.3140	0.0210
	KNN [10]	-	-	6.4300	-
	ELM [10]	-	-	1.9640	-
RBR [10]	-	-	0.7820	-	



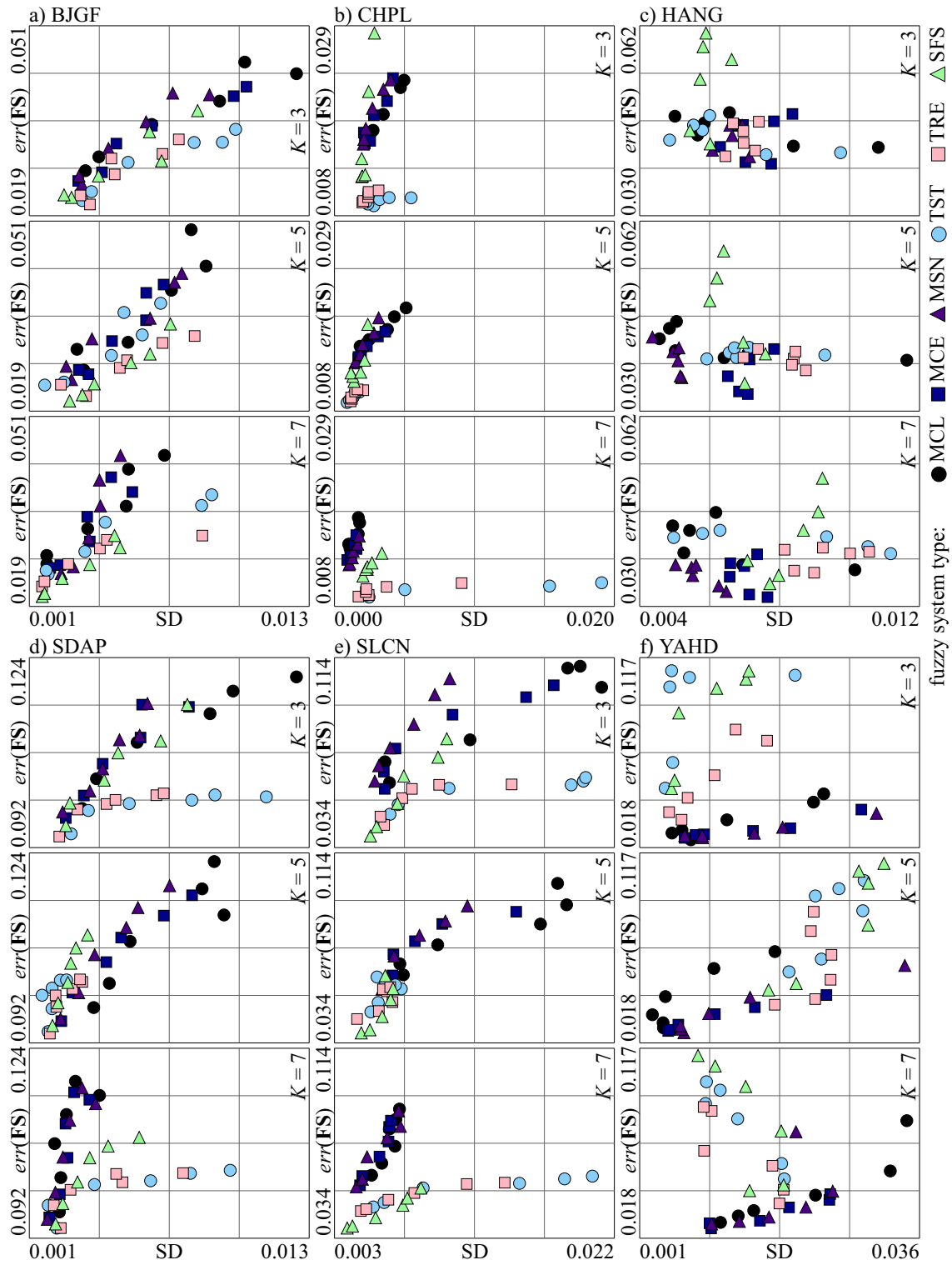


Figure A.4: Correlation between system error  $err(\mathbf{FS})$  and standard deviation  $SD$  for all considered problems and cases.

Table A.2: How many times a given system has achieved the best average results in terms of fitness function.

$\gamma =$	0.0	0.1	0.2	0.3	0.4	0.5	$\sum$
MCL	0	0	0	0	0	0	0
MCE	4	2	0	0	0	2	8
MSN	2	3	5	4	5	3	22
TST	3	4	3	4	3	3	20
TRE	4	2	3	5	6	6	26
SFS	5	7	7	5	4	4	32

Table A.3: How many times a given system has achieved the best average results in terms of system error.

$\gamma =$	0.0	0.1	0.2	0.3	0.4	0.5	$\sum$
MCL	0	0	0	0	0	0	0
MCE	4	4	4	1	3	3	19
MSN	2	2	2	4	2	3	15
TST	2	3	3	2	3	3	16
TRE	5	4	3	6	6	7	31
SFS	5	5	6	5	4	2	27

Table A.4: How many times an increase in number of fuzzy rules in given system has increased average accuracy.

$\gamma =$	0.0	0.1	0.2	0.3	0.4	0.5	$\sum$
MCL	9	8	10	9	11	7	54
MCE	9	9	11	8	9	9	55
MSN	9	9	8	7	8	7	48
TST	7	8	8	6	5	6	40
TRE	5	8	5	7	7	7	39
SFS	10	11	11	9	9	10	60

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