Enhancing Distributed Differential Evolution with a Space-Driven Topology

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***Abstract*—Differential evolution (DE) is a simple and efficient evolutionary algorithm for global optimization. In distributed differential evolution (DDE), the population is divided into several sub-populations and each sub-population evolves independently for enhancing population diversity as well as algorithmic performance. Sub-populations in DDE share their elite individuals with neighborhood through a predefined migration topology. However, the construction of traditional migration topologies does not consider the position information of sub-populations in the search space. The position information is helpful in controlling the degree of diversity between the sub-populations and their migrated individuals. A proper degree of diversity could promote the balance between exploration and exploitation for DDE algorithms. To achieve this target, a dynamic space-driven migration topology is proposed in this paper. The proposed topology is constructed and updated according to the distances between sub-populations. Based on this proposed topology, some sub-populations receive diverse individuals from neighborhood far away while others communicate with neighborhood nearby. Numerical experiments have been performed on 13 diverse test functions. Results verify the advantage of DDE with the proposed migration topology compared to those with classic topologies.**

I. Introduction

In the past decades, various kinds of evolutionary algorithms (EAs) such as differential evolution (DE) [1], [2], particle swarm optimization (PSO) [3], ant colony optimization (ACO) [4] have been developed. DE was proposed by Storn and Price [5], and has shown excellent performance on various types of optimization problems. It is widely acknowledged that a proper degree of population diversity is crucial for DE [6], [7]. To enhance the population diversity, distributed differential evolution (DDE) [8] has become one of the research directions.

In distributed differential evolution (DDE), population is partitioned into a number of sub-populations and each sub-population evolves independently toward a solution. With a given frequency, migration is performed and elite individuals of sub-populations are shared through a predefined migration topology. Due to the major impact on the performance of DDE [9], [10], [11], migration strategy is deserved to be sophisticatedly designed. To improve it, four aspects have been considered, namely, migration topology, migration interval, selection of migration and replacement. In this paper, we focus on the migration topology.

Three major types of migration topologies have been proposed in the existing DDE algorithms, namely, ring topology, random topology and mesh topology. Position information of sub-population in the search space is ignored in the construction of these traditional migration topologies. Without the position information, the degree of diversity between connected sub-populations could not be controlled. In this case, the search may lose the balance between exploration ability and exploitation ability. On the one hand, a sub-population is likely to get trapped into local optima if the incoming individuals are always from the same search region. On the other hand, stagnation is likely to occur when incoming individuals stay diverse.

To effectively control the degree of diversity between the sub-populations and their migrated individuals, a dynamic space-driven migration topology for DDE is proposed in this paper. A contribution-based core is newly defined to exactly locate the search region of each sub-population. With the help of these cores, the distance as well as the degree of diversity between two sub-populations could be measured. Motivated by the principle “not too similar, not too different” [12], the migrated individuals should neither too different from nor too similar to the sub-populations. Therefore, some sub-populations in the proposed topology are connected to the neighborhood far away, whose incoming individuals are diverse. Differently, some other sub-populations communicate with neighborhood nearby and receive similar individuals. Diverse individuals could enhance the exploration ability while similar individuals are helpful in exploitation. Since the search regions of sub-populations vary during the evolution, the proposed topology is updated with a given frequency according to the dynamic position information. In this way, a proper degree of diversity is achieved and contributes to the balance between exploration and exploitation for DDE algorithms.

The proposed dynamic space-driven migration topology could be applied to DDE variants for enhancing the performance. To verify the effectiveness of proposed migration topology, a number of experiments are carried out over 13 benchmark functions with various characteristics. Experimental results reflect that DDE with proposed migration topology

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This work was supported in part by the National Natural Science Foundation of China (NSFC) No. 61502544, No. 61332002, and No. 61300044, in part by the Open Project Program of the State Key Laboratory of Mathematical Engineering and Advanced Computing.

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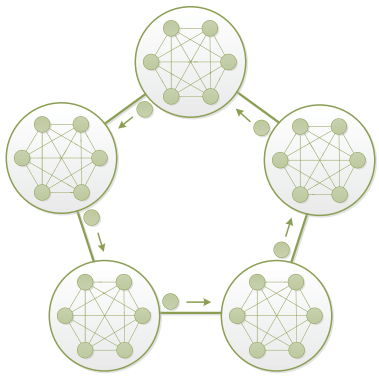


Fig. 1. Distributed Differential Evolution.

outperforms traditional migration topologies in terms of solutions, convergence and statistical tests. It is also shown that the proposed migration topology could enhance the performance of some well-known DDE variants.

The remainder of this paper is organized as follows. In Section 2, a review of related work on variants of migration topology is presented. Subsequently, Section 3 briefly introduces DDE. Section 4 describes the proposed DDE-SD algorithm in detail. Extensive experiments with discussion is provided in Section 5. Finally, Section 6 draws the conclusion.

II. Related work

In this section, a brief overview of traditional migration topologies is presented. Zaharie and Petcu presented a parallel distributed self-adaptive DE algorithm in [13], which used a random topology as the migration topology. Comparing versus a canonical DE, improvements of convergence have been obtained in the novel parallel model. Later, to improve both the speed and the performance in DE, a DDE with unidirectional ring topology was proposed by Tasoulis *et al.* in [8]. The experimental results indicated that the amount of information exchanged bears a significant impact on the performance of the algorithm. Based on the unidirectional ring topology in [8], several distributed methods were investigated. In [14], [15], the number of islands was studied. Furthermore, distributed islands in a toroidal mesh topology was used by Falco *et al.* in [16], [17], in which a chosen solution is sent to all the neighborhood. In the static ring and mesh topologies, the connections stay unchanged during the evolution. In the dynamic random topology, which is updated in every migration interval, the connections are built by random. The construction of these traditional migration topologies does not consider the position information of sub-populations in the search space.

III. Distributed Differential Evolution

In DDE, population is divided into a number of sub-populations and each sub-population evolves independently toward a solution. To promote information sharing, elite individuals of sub-populations are exchanged through the migration topology with a given frequency. We here take the procedure in PDE [8] as an example, which is a classic approach in DDE.

PDE algorithm adopts a DE/rand/1/bin algorithm, a best-random migration strategy and a unidirectional ring topology. As shown in Algorithm 1, during the migration, the best individuals from each sub-population are allowed to migrated to the next sub-population of the ring. Then these best individuals will take place of a randomly selected individual in the next sub-population. Fig. 1 shows how individuals are shared through the ring topology in PDE.

Algorithm 1 PDE Algorithm

Set the generation counter gen = 0
Generate the initial population P
Divide into N sub-populations
for $i = 1$ to N **do**
    Evaluate P^i and obtain the fitness set f^i
end for
while Terminal condition not reached **do**
    for $i = 1$ to N **do**
        Mutate P^i
        Crossover P^i
        Update P^i
        Evaluate P^i and obtain fitness set f^i
    end for
    if gen mod M == 0 **then**
        for $i = 1$ to N **do**
            Send best individual to the next sub-population
            Receive an elite individual from last sub-population
            Replace a randomly chosen individual
        end for
    end if
    gen = gen + 1
end while

IV. Dynamic space-driven migration topology

In this section, a dynamic space-driven migration topology for DDE is proposed, in which the position information of sub-populations in the search space is effectively utilized. In what follows, the motivation is presented firstly and then a contribution-based core is defined to help locate the search region of each sub-population. Subsequently, the approach to construct and update proposed topology is introduced in detail. Finally, an enhanced DDE with proposed space-driven topology (DDE-SD) is algorithmically illustrated.

A. Motivation

Considering migration has a significant influence on the performance of DDE, designing an appropriate migration strategy is helpful as well as challengeable. The focus of this paper is on the migration topology. In the traditional migration topologies, position information of sub-populations in the search space is ignored. Lacking of dynamic position

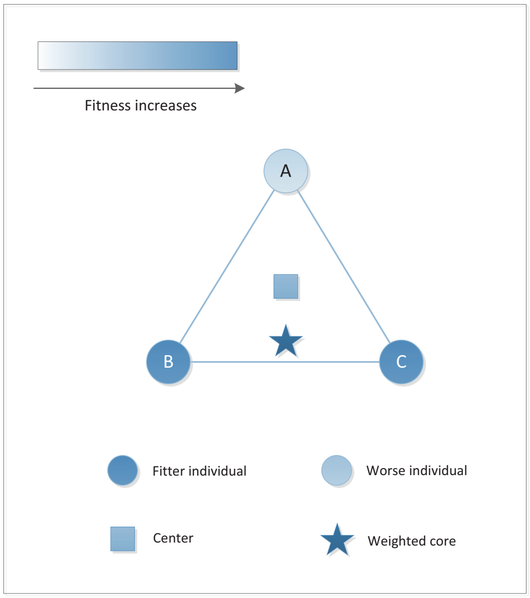


Fig. 2. Comparison of weighted core and center.

information means the degree of diversity between the sub-populations and their migrated individuals is unknown and uncontrolled.

In the proposed dynamic space-driven migration topology, a contribution-based core is defined to measure the search region of each sub-population. Then distance between two sub-populations could be calculated. The principle "not too similar, not too different" in [12] points out that somewhat different individuals are preferred in the natural mate-selection behavior. Motivated by this principle, in the proposed topology, some sub-populations communicate with neighborhood far away and receive diverse individuals. Differently, some other sub-populations are connected to near neighborhood and incoming individuals are similar. The former is helpful for exploration ability while exploitation ability is enhanced in the latter case. In this way, the degree of diversity as well as the balance between exploration ability and exploitation ability are effectively controlled.

B. Contribution-Based Core

In DDE, the search regions of sub-populations vary during the evolution. To locate the search region of a sub-population, positions of its individuals are firstly considered. Since the fitter individuals could always survive during the evolution in DE, the search direction would be affected by these fitter individuals. Based on this consideration, the cores to locate these search regions should also be closer to the fitter individuals. In the contribution-based core, both positions and fitness values of individuals are included.

In Fig. 2, a weighted core and a center of three individuals are shown. The weighted core considers both positions and fitness of individuals. The center only considers the positions of individuals. Unlike the center, the weighted core is closer to the fitter individuals as well as the search direction of these individuals.

Algorithm 2 DDE-SD Algorithm

Set the generation counter gen = 0
Generate the initial population P
Divide into N sub-populations
for $i = 1$ to N **do**
    Evaluate P^i and obtain the fitness set f^i
    Calculate the contribution core C^i
end for
Init the space-driven topology
while Terminal condition not reached **do**
    for $i = 1$ to N **do**
        Mutate P^i
        Crossover P^i
        Update P^i
        Evaluate P^i and obtain fitness set f^i
    end for
    if gen mod T == 0 **then**
        for $i = 1$ to N **do**
            Calculate the contribution core C^i
        end for
        Update the space-driven topology
    end if
    if gen mod M == 0 **then**
        for $i = 1$ to N **do**
            Send best individual to the neighborhood
            Receive an elite individual from the neighborhood
            Replace a randomly chosen individual
        end for
    end if
    gen = gen + 1
end while

C. Construction of Dynamic Space-Driven Topology

With the help of contribution-based core, the search region of a sub-population could be measutred. In this subsection, the approach to construct and update the proposed topology will be described in detail.

Firstly, based on the contribution-based cores, the distance between two sub-populations could be calculated. Subsequently, the proposed topology is constructed and updated according to these distances. The first sub-population is selected randomly. Then each new linked sub-population i chooses the farthest and unconnected sub-population j as the neighborhood. Finally, the last sub-population makes a connection with the first node to form a ring topology. Unlike always choosing the farthest sub-populations, the migrated individuals based on this topology are not too different from the sub-populations. This is because once a sub-population is inserted in this ring topology, it could not communicate with other sub-populations. Specifically, when sub-population i chooses sub-population, its farthest neighborhood might have been chosen

TABLE I
CHARACTERISTICS OF TEST FUNCTIONS.

Functions	**Characteristics**	**Dimension**	**MaxNFEs**
F_1, F_6, F_7	Unimodal, separable	100	1.00E+06
F_2, F_3, F_4, F_5	Unimodal, nonseparable	100	1.00E+06
F_9	Multimodal, separable	100	1.00E+06
F_8, F_{10}, F_{11}, F_{12}, F_{13}	Multimodal, nonseparable	100	1.00E+06

by others. Considering the search regions of sub-populations vary during the evolution, the proposed topology is frequently updated according to the latest position information. In this way, a proper degree of diversity could be achieved.

To improve the efficiency as well as enhance the stability of communication, rather than update the topology in every migration interval M, the proposed topology is updated in every shuffle interval T, which is longer than M.

D. DDE-SD

The proposed dynamic space-driven migration topology is embedded in DDE to develop DDE-SD algorithm, which adopts a DE/rand/1/bin algorithm and a best-random migration strategy. The pseudo code of DDE-SD is shown in Algorithm 2.

V. EXPERIMENTAL STUDIES

A. Experimental setup

In the experiments, 13 scalable functions in [18] are employed. Some characteristics of test functions are briefly summarized in Table I and more properties can be found in [18].

Three experiments are carries out in this section. The first experiment is used to verify whether the proposed topology could outperform the traditional topologies. The second experiment is carried out to reflect the effectiveness of proposed topology in some well-known DDE variants.

In DDE-SD, the mutation rate F and crossover rate C_r are set to 0.5 and 0.9 respectively, migration interval M is set to 20, and the update frequency of migration topology is set as $T = 200$. The whole population size NP of all the DDE algorithms is set as 200. The overall population is divided into $N = 10$ sub-populations.

B. Comparisons of classic migration topologies

In order to investigate the effectiveness of proposed migration topology, experiments are carried out to compare it with three classic migration topologies. DDE with the proposed topology is named DDE-SD and described in the last section. DDE algorithms adopting these three migration topologies are listed as follows:

1) DDE-random: the migration topology of DDE-SD is replaced by a randomly generated topology in [13].
2) DDE-ring: the migration topology of DDE-SD is replaced by a unidirectional ring topology in [8].
3) DDE-mesh: the migration topology of DDE-SD is replaced by a toroidal mesh topology in [16], [17].

The mean and standard deviations of the errors over 25 independent runs for all test functions are presented in Table II, where the best results are highlighted in boldface. Overall, DDE-SD achieves the best results in 9 functions, which is much higher than the figures 0, 3 and 1 of DDE-random, DDE-ring and DDE-mesh, respectively. We can conclude that our proposed migration topology comprehensively outperforms the traditional topologies.

To show the advantage of proposed migration topology in a statistical sense, single-problem Wilcoxon signed-rank test at a significance level 0.05 is performed. The errors for each function over 25 independent runs are used to conduct the test. As shown in Table II, where data in each cell is represented in a "$-/\approx/+$" manner, "$-$" "$\approx$" and "$+$" denote that the corresponding algorithm is significantly worse than, equivalent to and better than DDE-SD algorithm, respectively. It is clear that DDE-SD is able to obtain significantly better results than the other three approaches on the majority of functions.

In addition, the convergence curves of four approaches are plotted in Fig. 3. Namely, F_1, F_2 and F_7 are unimodal while the others are multimodal. Convergence curves of these six functions clearly show that DDE-SD converges fastest to achieve the highest solution accuracy among four approaches. On the one side, for unimodal functions, the proposed algorithm shows best exploitation ability. On the other side, in optimizing multimodal functions, DDE-SD exhibits much stronger global search ability than the other three algorithms. This is mainly because the balance between exploration ability and exploitation ability is effectively controlled in the proposed DDE-SD.

C. Cooperation with other DDE variants

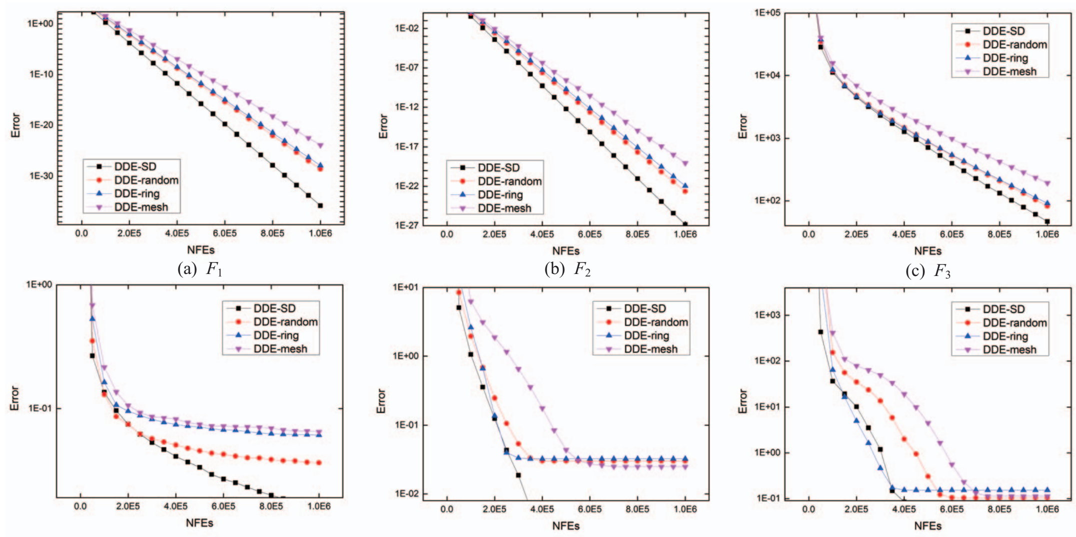
In this subsection, experiments are carried out to verify the effectiveness of the proposed migration topology on well-known DDE variants, namely, PDE and DDEM. Four approaches are developed and listed as follows.

1) PDE: a classic DDE adopts a DE/rand/1/bin algorithm, a best-random migration strategy and a unidirectional ring topology.
2) PDE-SD: the unidirectional ring topology in PDE is replaced by the proposed space-driven topology.
3) DDEM: a competitive DDE utilizes novel migration selection and replacement strategies [10].
4) DDEM-SD: space-driven topology is embedded in DDEM algorithm to replace the migration topology.

For each approach, 25 independent runs are carried out. Table III shows the results and the better results are marked in

TABLE II
COMPARISONS OF VARIOUS MIGRATION TOPOLOGIES.

Approaches	DDE-SD		DDE-random			DDE-ring			DDE-mesh		
	Mean	**Std**	**Mean**	**Std**		**Mean**	**Std**		**Mean**	**Std**	
F_1	**1.57E-36**	1.33E-36	2.51E-29	1.40E-29	$-$	1.28E-28	7.05E-29	$-$	1.39E-24	1.22E-24	$-$
F_2	**1.40E-27**	8.49E-28	2.27E-23	8.87E-24	$-$	1.12E-22	3.35E-23	$-$	9.01E-20	1.28E-19	$-$
F_3	**4.67E+01**	1.70E+01	8.25E+01	1.75E+01	$-$	9.13E+01	2.49E+01	$-$	1.93E+02	4.18E+01	$-$
F_4	2.12E+01	3.30E+00	2.07E+01	2.64E+00	$\approx$	**1.76E+01**	2.94E+00	$+$	2.86E+01	3.52E+00	$-$
F_5	**1.79E+02**	4.82E+01	2.08E+02	5.95E+01	$-$	1.84E+02	4.42E+01	$\approx$	2.03E+02	4.59E+01	$\approx$
F_6	6.40E+00	3.45E+00	3.72E+00	2.22E+00	$+$	**8.80E-01**	7.11E-01	$+$	2.06E+01	9.53E+00	$-$
F_7	**1.57E-02**	3.28E-03	3.64E-02	7.96E-03	$-$	6.10E-02	1.12E-02	$-$	6.49E-02	9.45E-03	$-$
F_8	**1.72E+04**	9.57E+02	1.81E+04	1.56E+03	$-$	2.08E+04	2.53E+03	$-$	1.74E+04	1.19E+03	$\approx$
F_9	**8.71E+01**	1.16E+01	8.82E+01	1.59E+01	$\approx$	9.38E+01	2.79E+01	$-$	9.57E+01	1.23E+01	$-$
F_{10}	7.26E-01	5.17E-01	7.09E-01	4.97E-01	$\approx$	**3.52E-02**	1.72E-01	$+$	1.89E+00	3.16E-01	$-$
F_{11}	1.58E-03	3.19E-03	1.58E-03	3.68E-03	$\approx$	1.58E-03	3.81E-03	$\approx$	**2.96E-04**	1.45E-03	$\approx$
F_{12}	**4.98E-03**	1.14E-02	3.02E-02	7.56E-02	$-$	3.24E-02	4.78E-02	$-$	2.49E-02	9.78E-02	$-$
F_{13}	**7.80E-02**	3.14E-01	1.04E-01	4.02E-01	$-$	1.53E-01	7.04E-01	$-$	1.13E-01	3.35E-01	$-$
$-/\approx/+$			8/4/1			8/2/3			10/3/0		



(a) F_1 (b) F_2 (c) F_3
(d) F_7 (e) F_{12} (f) F_{13}

Fig. 3. Convergence curves of DDE with various migration topologies.

bolt. It can be observed that, with the help of proposed space-driven migration topology, the performance of both PDE and DDEM algorithms is enhanced. Comparing PDE and PDE-SD, we can see that the latter performs better in 9 functions. Similarly, DDEM-SD could achieve higher performance than the original approach in most functions. To sum up, our proposed space-driven migration topology is efficient when cooperating with other DDE variants.

VI. CONCLUSION

Considering migration has a major impact on the performance of DDE, a dynamic space-driven migration topology is proposed to enhance DDE in this paper. In the traditional migration topologies, position information of sub-populations in the search space is ignored, which causes the degree of diversity between the sub-populations and their migrated individuals uncontrolled. In the proposed migration topology, a contribution-based core is newly defined to locate the search region of each sub-population. With the help of these cores, the distance as well as the diversity between two sub-populations could be calculated. The proposed topology is constructed and updated according to the distances between sub-populations. Based on the proposed topology, some sub-populations receive diverse individuals while others communicate with neighborhood nearby. The degree of population diversity as well as the balance between exploration ability and exploitation ability are effectively controlled. A number of experiments are carried out to verify the effectiveness of proposed topology. Experimental results show that the DDE with the proposed migration topology outperforms those with classic migration topologies.

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TABLE III
COOPERATION WITH WELL-KNOWN DDE VARIANTS.

Approaches	PDE-SD		PDE			DDEM-SD		DDEM		
	Mean	**Std**	**Mean**	**Std**		**Mean**	**Std**	**Mean**	**Std**	
F_1	**1.57E-36**	1.33E-36	1.28E-28	7.05E-29	$-$	**6.41E-32**	4.34E-32	5.73E-28	3.92E-28	$-$
F_2	**1.40E-27**	8.49E-28	1.12E-22	3.35E-23	$-$	**2.75E-24**	1.14E-24	7.80E-22	3.23E-22	$-$
F_3	**4.67E+01**	1.70E+01	9.13E+01	2.49E+01	$-$	**1.10E+02**	3.15E+01	1.35E+02	3.76E+01	$-$
F_4	2.12E+01	3.30E+00	**1.76E+01**	2.94E+00	$+$	**1.13E+01**	5.39E+00	1.18E+01	3.37E+00	$-$
F_5	**1.79E+02**	4.82E+01	1.84E+02	4.42E+01	$\approx$	1.81E+02	5.48E+01	**1.56E+02**	5.64E+01	$\approx$
F_6	6.40E+00	3.45E+00	**8.80E-01**	7.11E-01	$+$	1.68E+00	1.35E+00	**5.20E-01**	9.00E-01	$+$
F_7	**1.57E-02**	3.28E-03	6.10E-02	1.12E-02	$-$	**6.44E-02**	8.74E-03	9.00E-02	6.25E-03	$-$
F_8	**1.72E+04**	9.57E+02	2.08E+04	2.53E+03	$-$	**3.79E+04**	1.88E+04	1.72E+06	3.85E+06	$-$
F_9	**8.71E+01**	1.16E+01	9.38E+01	2.79E+01	$-$	**7.16E-01**	1.53E+00	2.75E+00	3.97E+00	$-$
F_{10}	7.26E-01	5.17E-01	**3.52E-02**	1.72E-01	$+$	**1.30E-05**	6.39E-05	3.03E-04	3.89E-05	$-$
F_{11}	1.58E-03	3.19E-03	1.58E-03	3.81E-03	$\approx$	1.77E-03	5.42E-03	**5.91E-04**	2.90E-03	$+$
F_{12}	**4.98E-03**	1.14E-02	3.24E-02	4.78E-02	$-$	**3.73E-03**	1.34E-02	8.71E-03	1.87E-02	$-$
F_{13}	**7.80E-02**	3.14E-01	1.53E-01	7.04E-01	$-$	**4.39E-04**	2.15E-03	1.46E-01	7.07E-01	$-$
$-/\approx/+$			8/2/3					10/1/2		

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