Swarm Behavior of the Electromagnetics Community as regards Using Swarm Intelligence in their Research Studies

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Abstract: Recently, swarm intelligence and its applications have gained much popularity among researchers of various disciplines. The main aim of this study is to investigate the situation for the electromagnetic theory and microwave technology practitioners and try to point to an interesting analogy.

Keywords: Swarm intelligence; ant colony optimization; particle swarm optimization; electromagnetic theory; microwave theory

1 Introduction

The term "swarm intelligence", since its introduction by Beni and Wang in 1989 in the context of cellular robotic systems [1], has been a major multidisciplinary attraction center for researchers dealing especially with complex inverse (e.g. design and synthesis) problems. Typically, swarm intelligence systems consist of a population with members having some characteristic behaviors and interacting locally with each other within their environment. In these systems, the members individually behave freely to a certain extent and interact with each other. Even though there is no dictating centralized mechanism, these interactions yield a global behavior which is more organized and directive than that of a stand-alone individual.

Today, two main algorithms come to mind when the phrase "swarm intelligence" is mentioned. These are the Ant Colony Optimization (ACO) (considered initially in 1992 by Dorigo in his Ph.D. thesis [2], and later formalized by Dorigo et al. in [3]), and the Particle Swarm Optimization (PSO) (developed by Kennedy and Eberhart in 1995 [4]) methods. Both algorithms were developed by researchers observing the behaviors of animals living as swarms/colonies and being inspired by them; and in more than a decade, they have proved to be successful in solving various complex problems due to their intelligent and systematic metaheuristic approaches. Originally, ACO was designed for combinatorial optimization problems, whereas PSO was designed for continuous ones. However, by now, successful versions of continuous ACO (e.g. [5-7]), and discrete PSO (e.g. [8-10]) have been developed.

ACO depends on the following principles: Initially, ants have random movements, but upon finding food they lay down pheromone trails returning home. Other ants have a tendency to follow these pheromones instead of keeping their random behavior. Over time, all pheromone trails start to evaporate and reduce their attractiveness. However, since pheromones over shorter paths are traced faster, and new pheromones are laid over the same path, the arate at which new pheromes are layed out surpasses the evaporation rate. Due to this positive feedback mechanism, the popularity of shorter paths (i.e. pheromone density) increases in an accelerated manner. This is the key of the success of the ACO for the solution of problems such as the traveling salesman problem.

On the other hand, PSO depends on the following main principles: The behavior of each individual in the swarm has three components, among which there is a balance. The first is random behavior (i.e. the tendency for searching and exploration), the second is social behavior (i.e. the tendency to observe and follow the other swarm members), and the final one is cognitive behavior (i.e. the tendency to revisit places of good memories). With these mechanisms, a swarm systematically searches the space, and the members are attracted rapidly to the best solution when found. This is the key of the success of PSO for the solution of multidimensional continuous optimization problems.

2 About the Analysis in this Study

It is a well known fact that swarm intelligence has gained much popularity and has diffused to a wide spectrum of research areas over the past two decades. Moreover, the increase in popularity and diffusion is still accelarating. A rough quantitative measure can be given as follows: As of July 2007, the number of citations of the 1995 dated original PSO proceeding (i.e. [4]) was about 1200 in Scopus, whereas as of January 2009, this number was almost 3000. Namely, the number of citations in the between July 2007 and January 2009 (a period of 1.5 years) is much more (almost 1.5 times) than the ones in the first 12 years.

In order to understand the rate of increase in the popularity of swarm intelligence among the electromagnetics community, an analysis of the publication archives was performed in this study. In fact, the results of a similar analysis were recently reported by Poli in a review article [11] (A more detailed version of Poli’s study is also available [12]). But unlike ours, the main aim of Poli's general-purpose study was to visualize the spread spectrum application areas of PSO, to identify each of these application areas, to construct an up-to-date PSO bibliography, and to perform taxonomy among the relevant publications. It is noteworthy that only the publications in IEEE Xplore database were included in Poli's analysis.

In this work, our main aim is to identify the increasing popularity of swarm intelligence (not only PSO, but also ACO) specifically among the electromagnetics community. Databases other than IEEE Xplore have also been included in the study. For this analysis, in addition to the major periodicals of electromagnetic theory and microwave technology, major general-purpose electrical/electronics engineering periodicals and the publications devoted to optimization and intelligence research have also been investigated. The periodicals included in this analysis are listed in Table 1. For a journal to be included in the analysis, the abstracting/indexing of the journal (i.e. the fact that the journal is being indexed in Thomson Scientific's Science Citation Index, Science Citation Index Expanded, etc.) were not considered, since there are many newly incepted journals which are not in some major indexes yet. The only restrictions for inclusion were that each journal would have ISSN numbers and would publish articles with original contributions after a peer-review process.

Since the archives of the major international symposium/conference proceedings are not as completely accessible and extensively searchable as the journal archives, the analysis was limited to journal and magazine publications. As another general rule, review articles were not accounted; only research articles were been considered.

By the time this analysis was performed, the results regarding the year 2009 were still immature; hence, the articles already published in 2009, or the ones with DOI but scheduled for publication in the upcoming issues in 2009 (i.e. articles in press) were not included in the analysis. For example, queries for Elsevier's *Expert Systems with Applications* returned one article which was still in press; hence, the relevant periodical is identified with a "×" (i.e. No Match) in Table 1.

For electromagnetic theory and microwave technology periodicals (e.g. *IEEE Transactions on Antennas and Propagation*, Taylor & Francis' *Electromagnetics*, etc.), any of the terms "swarm", "colony", "PSO", "ACO" (i.e. with the Boolean expression OR) was searched inside the Title, Abstract, and Keyword fields. The results of the queries were examined one by one in order to eliminate any occurrences of these terms for other purposes. For example, the query for *IEEE Transactions on Magnetics* returned some papers including the word "colony" of the "colony matrix" term, or the word "swarm" inside the "swarm points" term; such occurrences were identified and such papers were not accounted.

Table 1

List of investigated journals/magazines and information whether they have published papers/articles matching with the search criteria (*in alphabetical order with respect to the publisher*)

Publishing Institute / Company	**Related Journal / Magazine Name**	**Match**
ACES (American Computational Electromagnetics Society)	ACES Journal	√
AGU (American Geophysical Union)	Radio Science	×
Brno University of Technology	Radioengineering	√
CRL Publishing	Engineering Intelligent Systems	×
Electromagnetics Academy	PIER (Progress in Electromagnetics Research)	√
	PIERS Online	√
	PIER Letters	×
	PIER B	√
	PIER C	×
	PIER M	√
Electromagnetics Academy / Brill Publishing	Journal of Electromagnetic Waves and Applications (JEMWA)	√
Elsevier Science	AEÜ – International Journal of Electronics and Communications	√
	Applied Soft Computing	×
	Computers & Electrical Engineering	×
	Expert Systems with Applications	×
Emerald Group	The International Journal for Computational Mathematics and Electrical & Electronic Engineering (COMPEL)	×
ETRI (Korean Electronics and Telecommunications Research Institute)	ETRI Journal	×
Hindawi Publishing Corporation	International Journal of Antennas and Propagation	√
	International Journal of Microwave Science and Technology	×
	Journal of Artificial Evolution and Applications	√
IEEE (Institute of Electrical and Electronics Engineers)	Antennas and Propagation Magazine	√
	Antennas and Wireless Propagation Letters	√
	Microwave Magazine	×
	Microwave and Wireless Components Letters	×
	Transactions on Antennas and Propagation	√
	Transactions on Evolutionary Computation	×
	Transactions on Magnetics	√
	Transactions on Microwave Theory & Techniques	√
IEICE (Institute of Electronics, Information and Communication Engineers)	Electronics Express	×
	Transactions on Communications	×
	Transactions on Fundamentals of Electronics, Communications and Computer Sciences	×
IET (Institution of Engineering and Technology)	Electronics Letters	√
	Microwave, Antennas & Propagation	√
Inderscience Publishers	International Journal of Computational Science and Engineering (IJCSE)	×
	International Journal of Artificial Intelligence and Soft Computing (IJAISC)	×
IOS Press	International Journal of Applied Electromagnetics and Mechanics	√
John Wiley & Sons	Microwave and Optical Technology Letters	√
	International Journal of RF and Microwave Computer-Aided Engineering	√
	Expert Systems – The Journal of Knowledge Engineering	×
MIT Press	Evolutionary Computation	×
Research India Publications	International Journal of Computational Intelligence Research (IJCIR)	×

Table 1 (cont'd)

Schiele & Schön	Frequenz – Journal of RF Engineering and Telecommunications	√
Springer Verlag	Electrical Engineering (Archiv für Electrotechnik)	√
	Journal of Computational Electronics	×
	Radioelectronics and Communications Systems	×
	Swarm Intelligence	×
Taylor & Francis	Electromagnetics	√
	International Journal of Electronics	√
TÜBİTAK (The Scientific and Technological Research Council of Turkey)	Turkish Journal of Electrical Engineering and Computer Sciences (ELEKTRİK)	×
U.R.S.I. (Union Radio-Scientifique Internationale) Germany / Copernicus GmbH	Advances in Radio Science	√

For the general-purpose electrical/electronics engineering periodicals (e.g. Elsevier's *AEÜ – International Journal of Electronics and Communications*, IET's *Electronics Letters*, etc.) the same queries were performed. But in this instance, the query results were additionally examined in order to determine whether the applications in the studies were related to electromagnetic theory and microwave technology (by searching any of the terms "antenna", "propagation", "microwave", "electromagnetic", "wavelength" (i.e. with the Boolean expression OR) inside the Full Texts (or in Any Field if the feature is supported by the publisher's search engine)). The ones not related to electromagnetic theory or microwave theory were eliminated.

For the optimization and intelligence research periodicals (e.g. *IEEE Transactions on Evolutionary Computation*, Wiley's *Expert Systems*, etc.), in addition to the standard query, any of the terms "antenna", "propagation", "microwave", "electromagnetic", "wavelength" (i.e. with the Boolean expression OR) were also searched inside the Full Texts (or in Any Field if the feature was supported by the publisher's search engine). Similarly, the results of the queries were one by one examined in order to eliminate low relevancies.

Tables 2 and 3 list the annual distribution of the published articles in non-IEEE and IEEE periodical publications, respectively. It should be noted that the years before 1999 have also been included in the analysis; but since there are no publications in those years, they have been omitted in the tables for space considerations. In Figure 1, the total distributions can be seen as a bar graph.

Table 2

Number of electromagnetic theory related papers/articles using swarm intelligence (periodicals not published by IEEE) - (*order of appearance as in Table 1*)

Journal / Magazine Name	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**Journal Total**
ACES Journal				1				1		**2**
Radioengineering			1			2	2	1	2	**8**
PIER (Progress in Electromagnetics Research)								3	6	**9**
PIERS Online									1	**1**
PIER B									2	**2**
PIER M									1	**1**
Journal of Electromagnetic Waves and Applications (JEMWA)			1		1	1	2	3	2	**10**
AEÜ – International Journal of Electronics and Communications									1	**1**
International Journal of Antennas and Propagation									1	**1**
Journal of Artificial Evolution and Applications									1	**1**
Electronics Letters						1		1	3	**5**
Microwave, Antennas & Propagation								1		**1**
International Journal of Applied Electromagnetics and Mechanics								2		**2**
Microwave and Optical Technology Letters				1		2	6	7	4	**20**
International Journal of RF and Microwave Computer-Aided Engineering			1				1	2	2	**6**
Frequenz – Journal of RF Engineering and Telecommunications									1	**1**
Electrical Engineering (Archiv für Electrotechnik)		-							2	**2**
Electromagnetics							2	1	2	**5**
International Journal of Electronics					1					**1**
Advances in Radio Science							1			**1**
ANNUAL TOTAL	**0**	**0**	**3**	**2**	**2**	**6**	**14**	**22**	**31**	**80**

Table 3

Number of electromagnetic theory related papers/articles using swarm intelligence (periodicals published by IEEE) - (*order of appearance as in Table 1*)

Journal / Magazine Name	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**Journal Total**
Antennas and Propagation Magazine							1	1		**2**
Antennas and Wireless Propagation Letters						1	6	2	1	**10**
Transactions on Antennas and Propagation					2	5	2	11	7	**27**
Transactions on Magnetics			2		1	3	4	3	8	**21**
Transactions on Microwave Theory & Techniques						1			1	**2**
ANNUAL TOTAL	**0**	**0**	**2**	**0**	**3**	**10**	**13**	**17**	**17**	**62**

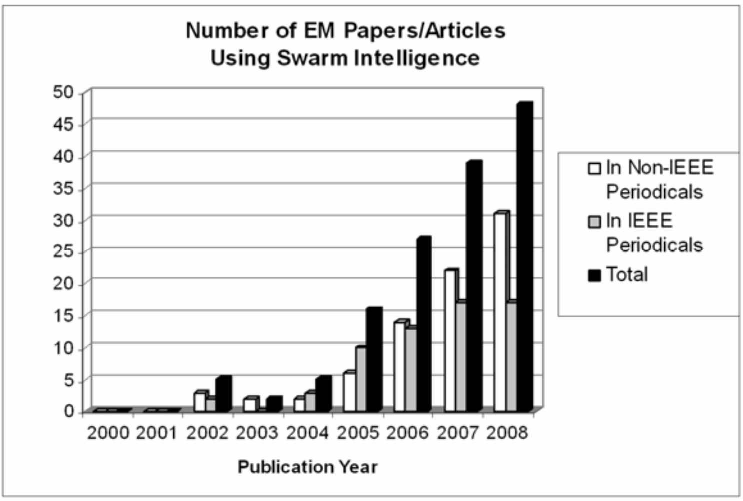

Figure 1

Annual increase in number of electromagnetic theory related journal papers/articles using swarm intelligence

3 The Analogy

Roughly speaking, the behaviors of all researchers resemble swarms and colonies, and the following analogies can be claimed.

From the ant colony perspective, a researcher lays out virtual pheromones to the "optimal publication" paths, where this optimality depends on his/her own personal criteria. In other words, most of the time, such criteria determine the address of submission for new manuscripts. These criteria might be the aim and scope, turn-around time, abstracting/indexing, the impact factor of the journal, interest and timing matches with any special issues, the tendency of the editorial/advisory board to the subject, etc. Optimal publication paths are attractive not only for that researcher but also for his fellows or any other researcher with similar areas of interest.

On the other hand, from the particle swarm optimization perspective, each researcher in the academic world has the tendency to explore new research areas, the application of novel methods to existing problems, etc. (i.e. random search and exploration behavior). At the same time, each researcher has the tendency to observe and follow the new trends, approaches, methods and applications in his/her own research area (i.e. social behavior) by means of tracking up-to-date literature. Moreover, each researcher has the tendency to revisit and extend his previous critically acclaimed and highly cited studies in order to create new publications (i.e. cognitive behavior).

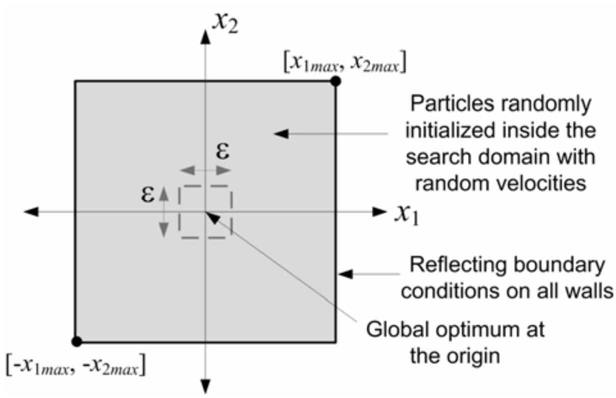

Figure 2
The two-dimensional search domain for the optimization problems

All the above facts are sufficient for a qualitative (and more or less subjective) analogy between the swarm/colony members and scholars. For a quantitative figure of the merit the the analogy, the following analysis was performed. Two-dimensional benchmark problems were solved by means of the particle swarm optimization, for which the search space is seen in Figure 2. For position and velocity updates in each iteration, the formulation of Shi and Eberhart [13] was used:

$$v_n = c_1 v_n + c_2 u_1 (pbest - x_n) + c_3 u_2 (gbest - x_n) \tag{1}$$

$$x_n = x_n + \Delta t v_n \tag{2}$$

where v_n is the velocity component of the particle in the nth dimension, and x_n is its coordinate at the nth dimension. Certainly, these two operations are repeated for both dimensions. In these equations; the so-called inertial weight c_1, is a measure indicating the tendency to preserve the velocity along the previous course. Although not existing in the original PSO paper [4], inertial weight was introduced later by Shi and Eberhart [13] in order to improve the performance of the method; moreover, they showed that the ideal choice for the inertial weight is to decrease it linearly from 0.95 to 0.4 [14]. c_2 and c_3 are measures indicating the tendencies to converge to the *pbest* and *gbest*, which are the personal and global best positions, respectively. In early PSO researches, c_2 and c_3 were usually chosen to be 2.0; whereas for recent works 1.494 seems to be a more preferred value. u_1 and u_2 are random numbers between 0.0 and 1.0. The step size in time Δt is chosen to be unity for simplicity. The particles are kept inside the search space by means of the reflecting boundary conditions defined by Xu and Rahmat-Samii [15]. It is also common practice to put limitations to the velocities of the particles, since there is a probability that overspeedy particles jump over the global optimum. In this study, $|v_{n,max}|$ is set to 0.005.

As a first problem, global optimum for the two-dimensional sphere function (i.e.

$$f(\mathbf{x}) = \sum_{i=1}^{n} x_i^2 \tag{3}$$

where n=2) was searched; for which the number of particles inside ε vicinity of the global optimum at each iteration is investigated. It is expected that once the global optimum is found by any member, the others will be quickly attracted to that point. In order to have a more robust experiment, 1000 independent PSO executions were performed. The number of particles was taken to be 100; and the number of iterations was set equal to 100. The search space was chosen to be a square [-5000.0, 5000.0] × [-5000.0, 5000.0], where ε is chosen to be 0.1. For all independent executions, the global optimum was found by the swarm accurately (i.e. all the parameter settings mentioned in the previous paragraph and this paragraph were appropriate). The variation of the number of particles attracted to the global optimum (averaged over all executions) vs. the iteration is seen in Figure 3.

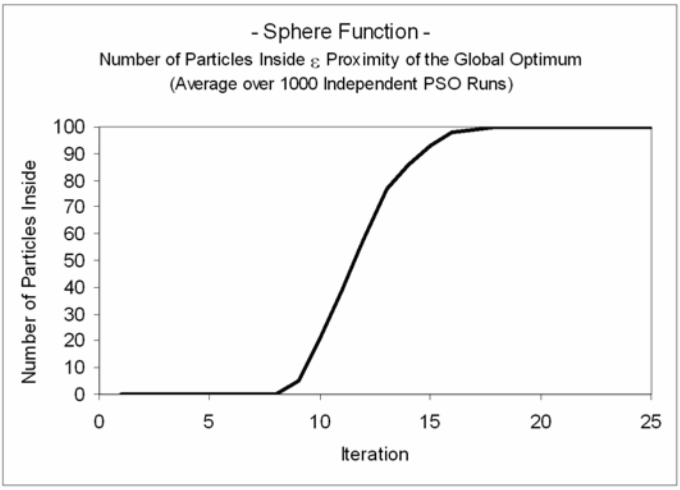

Figure 3
Number of particles around the global optimum vs. iteration for the two-dimensional sphere function

As a second problem, global optimum for the two-dimensional Rastrigin function (i.e.

$$f(\mathbf{x}) = 10n + \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i)) \quad (4)$$

where n=2) was searched. Again, 1000 independent PSO executions were performed. This time, the number of particles is 100; and the number of iterations is 500. The search domain is a square [-5.12, 5.12] × [-5.12, 5.12], where ε is chosen to be 0.1. For all independent executions, the global optimum was found by the swarm accurately (i.e. all the parameter settings were appropriate). The variation of the number of particles attracted to the global optimum (averaged over all executions) vs. the iteration is seen in Figure 4.

Finally, the bar graph seen in Figure 1 is redrawn as an *XY*-line chart in Figure 5, where the years 1995-1999 are also added. As we see in Figure 3, for the sphere function, the number of particles around the global optimum is monotonically increasing. Moreover, the second derivative of the curve for the initial ramp-up phase is positive. With the parameter setup, 20-25 iterations became sufficient for the whole swarm to be attracted around the global optimum. This is most probably because of the fact that there are no local minima for the sphere function.

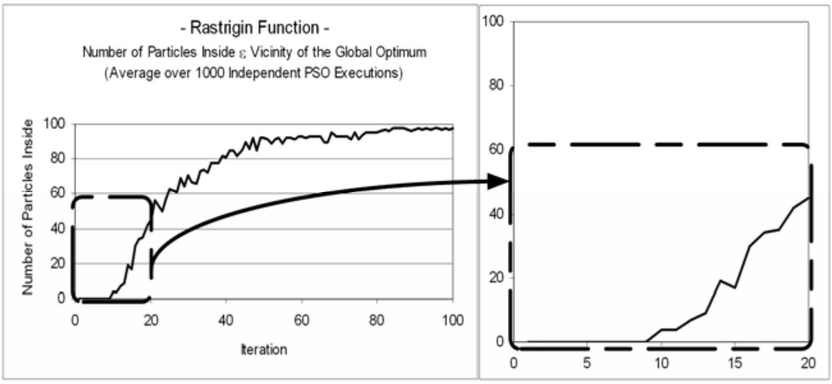

Figure 4
Number of particles around the global optimum vs. iteration for the two-dimensional Rastrigin function

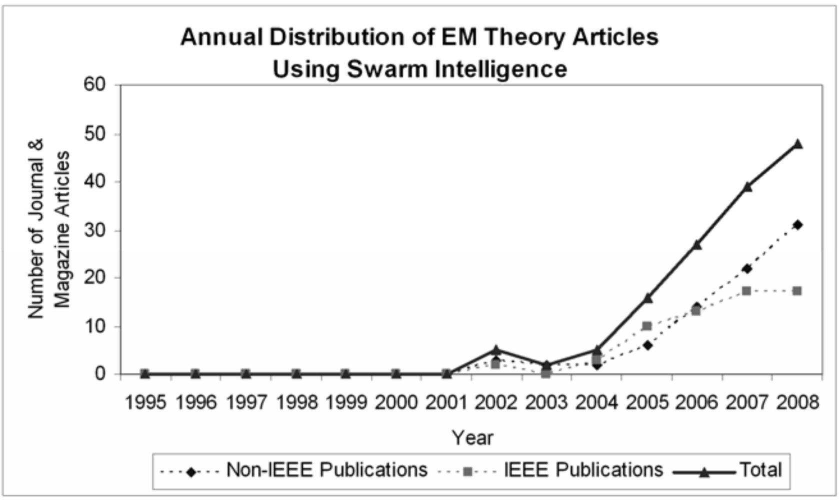

Figure 5
The *XY*-line chart version of the graph seen in Figure 1

For the Rastrigin function, on the other hand (Figure 4), even though there is an overall increase in the curve, it can be seen that there are fluctuations at some points. In addition, although there is an accelerated ramp-up phase, it is not as smooth as in the sphere function case. Moreover, it takes more time for the whole swarm to be attracted to the global optimum. This is most probably because of the fact that there are multiple local optima for the Rastrigin function; and sometimes some particles are erroneously but temporarily attracted backwards by one of the local optima.

Comparing the characteristics of Figures 3, 4, and 5, we can see that for all cases it takes some time for any swarm member to encounter the optimum; and an attraction center is created afterwards. More specifically, the detail of Figure 4 is very similar to Figure 5 in character. This means that the behavior of the electromagnetics community resembles the behavior of the particles which search the global optimum of a multimodal function. This makes sense, since there are researchers (particles) which are sometimes temporarily attracted to other interesting research areas and topics (optima); and this causes fluctuations in the number of swarm intelligence related published articles.

Finally, a rough guess by looking at Figure 3, 4 and 5 can be made as follows: the number of such publications might be continue increasing over the next 5-10 years.

Conclusions

In this study, the behavior of the electromagnetics community as regards using swarm intelligence in their research studies is analyzed. It is observed that the attraction of the subject is similar to the attraction of a global optimum of a multimodal function; and the movements of the researchers are similar to those of swarm members. Although the "swarm intelligence" topic is semi-humorously chosen in this study, "the fact of being an attraction center" can be generalized to any promising new method or technique. Moreover, this type of behavior is not unique for the electromagnetics community; it is also applicable for other societies of various disciplines.

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