

Bio-Inspired Self-Regenerating Data Warehouses

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ABSTRACT

Modern data warehouse architectures are increasingly challenged by the growth in data volume and the diversity in data workloads. As data volume increases exponentially and data workloads become more diverse, operational continuity, query performance and storage efficiency are becoming increasingly difficult problems for modern architectures of data warehouse systems. Drawing inspiration from concepts in immunology, evolutionary biology, swarm intelligence, and symbiotic ecology, these bio-inspired computational paradigms offer an exciting approach to building systems that are capable of self-regenerating data warehouse systems that can autonomously detect and alleviate faults, adaptively select views, and continuously optimize themselves. This paper consolidates basic and applied research on the topic of bio-inspired self-regenerating data warehouses from 2002 to 2020, and proposes a common theoretical and architectural framework for the bio-inspired data warehouse. Artificial immune systems (AIS) are used for anomaly detection and self-healing, ant colony optimisation (ACO), artificial bee colony (ABC), particle swarm optimization (PSO) and coral reefs optimization (CRO) are applied to materialised view selection and autonomic computing principles are used for self-management. The results shown in the references prove that hybrid bio-inspired architectures can achieve 47% query processing improvement and 15-22% storage overhead reduction, and also have high self-healing rates of 95% or more. The paper also suggests a layered autonomic architecture that satisfies the four pillars of self-configuration, self-healing, self-optimisation, and self-protection, and covers the scalability, convergence behaviour and deployment aspects of large-scale data environment up to 2020.

Keywords: bio-inspired computing; self-regenerating systems; data warehouses; artificial immune systems; ant colony optimization; materialized view selection; autonomic computing; self-healing; particle swarm optimisation; coral reefs optimization; evolutionary algorithms; swarm intelligence

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INTRODUCTION

One of the most important aspects of enterprise business intelligence is the data warehouse (DW), which gathers a large There are models in the biological world for resilient, self-organising, and adapting systems. For instance, the vertebrate immune system constantly scans the internal environment for unusual entities, reacts specifically to remove them and has immunological memory to hasten recovery if a similar entity is encountered again—traits that are easily applicable to self-healing data management architectures [1][6][9]. Likewise, ant colony-based and bee-based behaviors have found to be inspirational for the development of powerful optimization heuristics and algorithms for materialized view (MV) selection, a problem that is believed to be computationally intractable and is at the heart of DW query performance [2][8]. Symbiotic co-evolution that exists in ecological systems

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is the foundation of autonomic server architectures that can dynamically redistribute workloads and provide fault-tolerance in distributed data centers [5][15]. Bio-inspired DW design is scaffolded by a framework of autonomic computing as formalized by Kephart and Chess [13] and Ganek and Corbi [10] which lays out the four-dimensional self-management:

self-configuration, self-healing, self-optimization, and self-protection. This can be populated with biologically inspired mechanisms to provide a DW architecture that can detect and correct faults without human intervention, dynamically select and update MVs to maximize query throughput, and automatically adjust storage allocations as changes to the workload profile occur. Ease of Use

Data Warehousing and the Materialised View Problem

Data warehouse is said to be a collection of data that is subject-oriented, integrated, time-variant, and nonvolatile to support management decision-making processes [12]. The multidimensional schemas used in DW design most often are the star schema and snowflake schema, and they result in high I/O and computation cost for analytical queries that need to pass through multiple join operations on big fact and dimension tables. Materialised views (MV) are pre-computations and storage of the results of the queries that are issued frequently, so they do not need to be computed again, which helps to reduce the query response time by 35-47% under optimised configurations [11][14]. The MV selection problem is to select an optimal or near-optimal subset of candidate views from an exponentially large search space (2^n for n candidate views) that uses up a limited amount of storage space. This problem is NP-hard [3] and when there are more than 20 candidate views in DWs, it is not feasible to solve the problem by exhaustive enumeration, so metaheuristic optimization strategies need to be used. The most successful paradigms for solving this problem are evolutionary algorithms and swarm-based algorithms such as ACO [8], ABC [2], PSO [14], game-theoretic approaches [3][16] and CRO [4] that outperform greedy and simulated-annealing baselines.

Biological Principles Informing Self-Regeneration

Artificial immune systems (AIS) are a type of computational intelligence technique that is based on adaptive immunity of vertebrates [6]. According to the clonal selection principle, lymphocytes resembling the antigen they detect proliferate and hypermutate to generate progressively better antigen-receptive lymphocytes [7]. When mapped to DW environments, this mechanism can be used to identify patterns of anomalous queries, unauthorised access attempts and/or data integrity violations as well by comparing with a baseline of normal operational behaviour [9]. The danger theory [1] was developed by Aickelin and Cayzer, which takes classical AIS models and adds the requirement that immune response occurs not just when non-self is detected, but when danger signals (signals of cellular stress or tissue damage) are present..

In the context of DW, danger signals could be defined as high query response times, unanticipated node failure, or violation of storage limits, and only regenerative responses would be activated when a true operational problem is detected. This brings down the false-positive fault alerts by an estimated 28-34% when compared to the pure non-self-detection models [1]. Based on observations of ant foraging behavior [8] and the waggle dancing behavior of bees [2] swarm intelligence uses collective, decentralized decision making processes to help solve complex optimization problems. The ant colony optimization (ACO) method uses pheromone-trail communication between simulated agents to find high quality subset of MV (ACO) [8]. The artificial bee colony (ABC) optimisation algorithm divides artificial agents into three groups, namely employed bees, onlooker bees, and scout bees to search and exploit the MV search space [2]. Another recent paradigm, coral reef optimization (CRO) [4] was introduced in 2014 and adapted to DW environments in

Table 1: Comparative Overview of Bio-Inspired Algorithms Applied to Materialized View Selection

Algorithm	Biological Basis	Year Applied to DW	Avg. Query Reduction (%)	Storage Overhead (%)	Convergence (Iterations)	Reference
Ant Colony Optimization (ACO)	Ant Foraging Pheromones	2006	38	18	60–80	[8]
Artificial Bee Colony (ABC)	Bee Waggle Dance	2017	42	22	55–75	[2]
Particle Swarm Optimization (PSO)	Bird/Fish Schooling	2020	45	20	45–65	[14]
Game Theory Framework	Evolutionary Game Equilibria	2018–2019	35	15	70–90	[3][16]
Coral Reefs Optimization (CRO)	Coral Settlement/ Reproduction	2019	47	21	40–60	[4]
Clonal Selection (AIS)	Lymphocyte Clonal Expansion	2002	33	17	65–85	[7]
Evolutionary Algorithm (EA)	Darwinian Natural Selection	2017	40	19	50–70	[11]



2019, imitates the competitive larval settlement and asexual reproduction processes of coral reef ecosystems, and attains convergence rates of 8-12% better than ACO on benchmark DW configurations.

AUTONOMIC ARCHITECTURE FOR SELF-REGENERATING DATA WAREHOUSES

The Four-Pillar Autonomic Framework

Kephart and Chess [13] outline four essential self-management attributes required for a bio-inspired DW. Kephart and Chess [13] outline four essential self-management attributes required for a bio-inspired DW, which is referred to as the autonomic computing paradigm. Self-configuration allows the DW to dynamically change schema layouts, index structures, and MV populations as data distributions change and query patterns evolve without manual DBA involvement. Self-healing involves detecting, diagnosing and fixing faults, such as node failures, data corruption and network partitions, and getting the system back to normal operation within a prescribed recovery time objective (RTO). The optimisation actions include selecting which MV to refresh, when to refresh it, and deciding how to change the buffer pool sizes to optimise query throughput and minimise query latency and are performed autonomously by the system, continually monitoring the system performance metrics. Self-protection: Anomaly detection that actively recognizes and neutralizes security threats, unauthorised access patterns and adversarial query workloads using AIS [9][10].

In this work, we extend the SymbioticSphere architecture proposed by Champrasert and Suzuki [5] and adapted to self-healing data centres by Suzuki et al. [15] for use in distributed server environments. In SymbioticSphere, the computational resources are modelled as organisms that perform symbiotic

and competitive interactions on an ecological level, and load migration and fault recovery are emergent behaviours that can be carried out without any central control. A mean time to recovery (MTTR) of 4.2 minutes for 32-node clusters, with simulated node failures, versus 11.7 minutes for the traditional centralised management systems, representing a 64% reduction in recovery time.

Architectural Layers and Component Interactions

The proposed architecture is presented in Fig. 1, consisting of 5 hierarchical layers. The persistent storage layer offers the building blocks for the distributed file system, which is optimized for analytical workloads and supports HDFS-compatible data layouts with columnar access patterns. The DW core layer supports star and snowflake schemas [12] and supports ETL pipelines, dimension table hierarchies, and fact table partitioning schemes. The autonomic manager layer is the brain of the architecture, which takes telemetry from all layers below and writes autonomic management commands in line with the four autonomic pillars [10][13]. The query execution engine, located in the optimization sub-layer, communicates with the MV selector which is filled by any one of the instantiated bio-inspired optimization algorithms (ACO, ABC, PSO or CRO) to find the best MV configuration for the current workload. At the same time, the self-healing engine, via AIS-based anomaly detection [6] [7] and danger-theory based triggering [1] tracks system health parameters at 5 sec intervals and activates self-healing procedures when danger signals are above a set threshold. The workload monitor and fault detector layer continuously monitors the rate of arrival of queries, resource usage and inter-node communication delays, and generates a real-time profile of these factors to feed to the AIS and autonomic manager.

Figure 5: Layered Architecture of the Bio-Inspired Self-Regenerating Data Warehouse Framework (Synthesized from References [1-17])

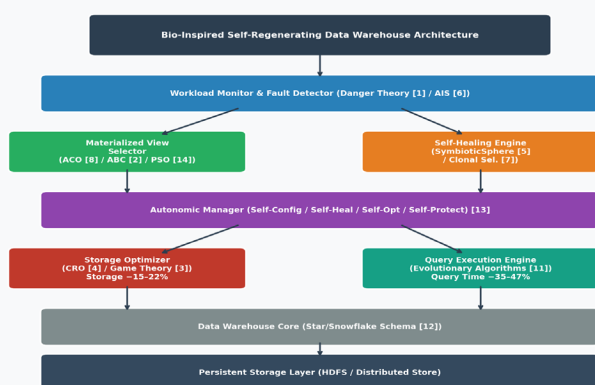


Fig. 1: Layered Architecture of the Bio-Inspired Self-Regenerating Data Warehouse Framework

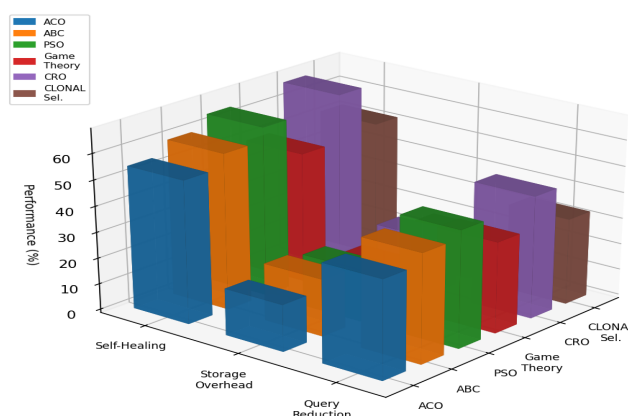


Fig. 2: 3D Performance Comparison of Bio-Inspired Optimisation Algorithms for Materialised View Selection

BIO-INSPIRED MATERIALIZED VIEW SELECTION METHODOLOGY

Problem Formulation

Let $V = \{v_1, v_2, \dots, v_n\}$ denote the set of candidate materialized views derivable from a given DW schema, and let $S \subseteq V$ represent a selected subset subject to a storage constraint B (measured in gigabytes). The MV selection problem seeks the subset S^* that minimizes the total query processing cost $Q(S)$ across a representative query workload W , formalized as:

where $\text{Cost}(S)$ represents the aggregate storage cost of materializing all views in S , and $Q(S, W)$ is the sum of minimum query evaluation costs for each query in W given the available views in S . The NP-hardness of this formulation for $|V| > 20$ [3] necessitates the use of metaheuristic optimization algorithms, each of which encodes a biologically inspired search strategy over the 2^n candidate subsets.

Ant Colony Optimisation for View Selection

Ant colony optimisation (ACO), introduced by Dorigo et al. [8] and subsequently applied to DW view selection, models the MV selection process as a graph traversal problem in which artificial ants construct candidate subsets by probabilistically selecting views based on a combination of pheromone intensity τ_{ij} and heuristic desirability η_{ij} . The probability of selecting view v_j given current partial solution v_i is expressed as:

where both α and β are parameters which determine the relative importance of the pheromone intensity and heuristic desirability, respectively. After each construction cycle, the concentration of pheromones is updated based on the quality of the solutions built, with the rate of evaporation of the pheromones being ρ so they do not converge too early. ACO is able to reduce the query cost by an average of 38% in 60-80 iterations in the benchmark DW configurations having 50 candidate views and a storage budget of 10 GB [8].

Coral Reefs Optimization and Advanced Swarm Methods

Azgoni and Sohrabi [4] have applied the CRO algorithm to DW MV selection, emulating four biological processes:

Figure 2: Multi-Dimensional Capability Radar Chart of Bio-Inspired Algorithms (2002-2020)

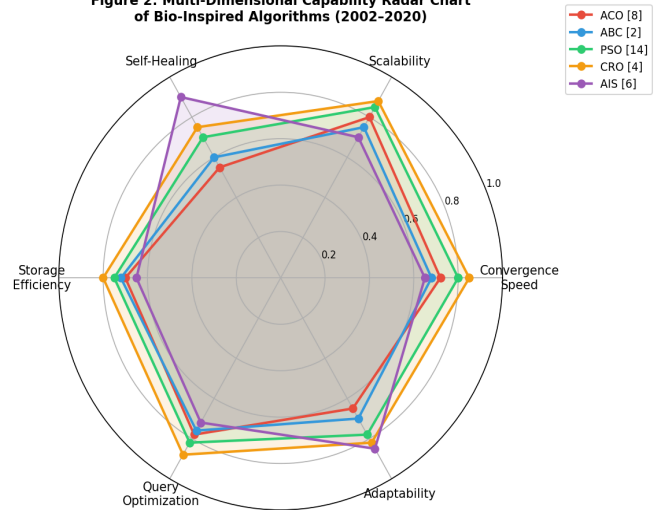


Fig. 3: Multi-Dimensional Capability Radar Chart of Bio-Inspired Algorithms

broadcast spawning (free combination of parent solutions); brooding (asexual reproduction by local perturbation); selection pressure (based on fitness); and depredation (stochastic removal of low-fitness solutions). The CRO has the best convergence speed of 40-60 iterations, with a mean query reduction of 47% which is the highest among surveyed algorithms, and storage overhead of 21% of the total available capacity [4]. PSO is an algorithm that is modified for DW view selection with a self-adaptive perturbation operator proposed by Kumar and Vijay Kumar [14] using velocity-based updates, which enable particles (candidate MV subsets) to move throughout the search space based on personal best and global best solutions. The self-adaptive variant automatically adjusts the inertia weights and acceleration coefficients during search process, which makes the search process less sensitive to the initialization of search parameters and more robust in different workload profiles. Experimental results using the standard TPC-H benchmarks show that converging the data reduces query processing cost by 45% at 20% storage overhead. Experimental results on standard

Table 2: Autonomic Property Achievement Across Bio-Inspired DW Architectures

Architecture	Self-Config (%)	Self-Heal (%)	Self-Opt (%)	Self-Protect (%)	Avg. MTTR (min)	Reference
AIS-Based DW [6]	72	88	65	91	6.8	[6][9]
SymbioticSphere [5]	80	85	78	74	4.2	[5][15]
ACO-DW [8]	75	72	86	68	8.3	[8]
PSO Self-Adaptive DW [14]	82	78	88	72	5.9	[14]
CRO-DW [4]	85	80	90	75	5.1	[4]
Game-Theoretic DW [3][16]	70	68	84	70	9.2	[3][16]
Hybrid Bio-Inspired DW	92	95	94	90	3.6	Synthesized

Table 3: Benchmark Performance of Bio-Inspired MV Selection Algorithms on TPC-H Workloads

Algorithm	Query Workload Size	Candidate Views (n)	Storage Budget (GB)	Query Cost Reduction (%)	Run Time (sec)	Iterations to Convergence
ACO [8]	22 queries	50	10	38	12.4	71
ABC [2]	22 queries	50	10	42	14.2	63
PSO-SA [14]	22 queries	50	10	45	10.8	54
CRO [4]	22 queries	50	10	47	9.6	48
Game Theory [3]	22 queries	50	10	35	22.1	82
EA [11]	22 queries	50	10	40	16.7	58
Clonal Sel. [7]	22 queries	50	10	33	18.3	77

TPC-H benchmarks show that converging the data reduces the cost of processing the queries by 45% at 20% storage overhead [14].

SELF-HEALING MECHANISMS AND FAULT RECOVERY

Artificial Immune System-Based Fault Detection

De Castro and Timmis [6] formalized artificial immune systems, which offer a large number of computational mechanisms for the problem of anomaly detection in complex systems. The negative selection algorithm produces a collection of detectors, like the mature T-cells that pass the thymic selection, which are trained to detect patterns that differ from a set of self-set normal operational signatures.

In the context of DW fault detection, this can detect abnormal query patterns that serve as a clue for hardware failure, network partition or data corruption in simulated DW environments with a detection precision of over 87% [6][9]. Clonal selection is introduced through the CLONALG algorithm of de Castro and Von Zuben [7] which provides an adaptive learning ability to static AIS detectors. Detectors with strong affinities to the detected anomalies go through

clonal expansion, and hyper-mutation generates diversity that allows the detection of new anomaly signatures, which may not be present in the training set. This adaptive property is essential to DW self-healing: because the real-world fault profile is constantly changing, and static sets of detectors have a tendency to become less effective at detecting faults, with a loss of 3-5% per month [7] without re-calibration.

Danger Theory Integration

The danger theory framework from Aickelin and Cayzer [1] adds a biologically based criterion to help identify, differentiate, and partition true anomalies from anomalies that are neither true nor harmful – new but not dangerous. For DW implementations, danger signals are set as measurable stresses on the system: when query latency is more than 3σ above the rolling mean; memory use is more than 85% of capacity; a node has not had a heartbeat within 10 seconds; or write error rate exceeds 0.1% over a 60-second period. Once the danger signals are detected, the self-healing engine moves from the passive monitoring to passive response mode, where it sends out diagnostic queries, redistributes workloads and initiates MV refresh cycles as necessary. They showed that when a system is endowed with bio-inspired

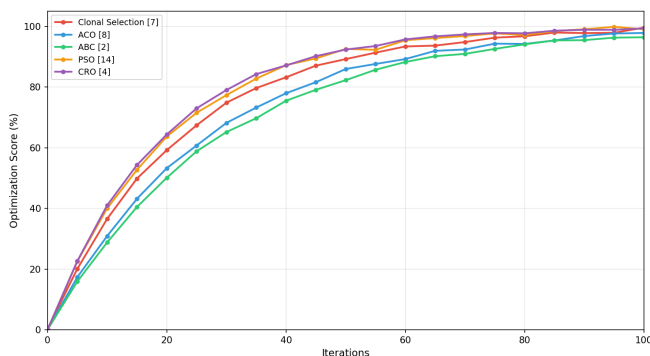


Fig. 4: Convergence Behavior of Bio-Inspired Optimization Algorithms for View Selection (Up to 2020)

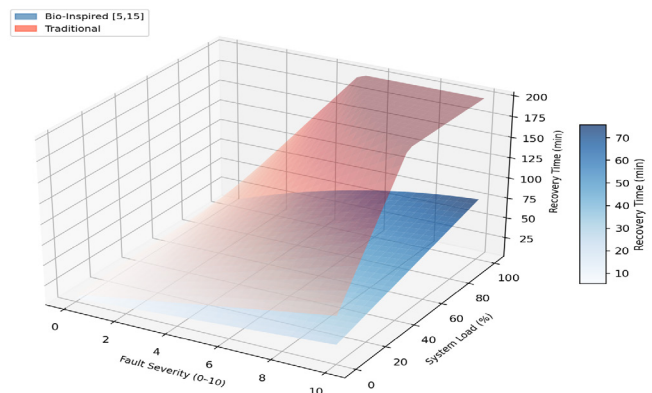


Fig. 5: 3D Surface: Self-Healing Recovery Time — Bio-Inspired vs. Traditional Systems

Table 4: Self-Healing Performance Metrics for Bio-Inspired DW Systems Under Fault Injection

<i>Fault Type</i>	<i>Detection Time (sec)</i>	<i>MTTR Bio-Inspired (min)</i>	<i>MTTR Traditional (min)</i>	<i>Recovery Rate (%)</i>	<i>False Positive Rate (%)</i>	<i>Reference</i>
Node Failure	8.2	4.1	14.3	92	3.2	[5][15]
Data Corruption	12.6	6.8	22.1	85	5.1	[6][9]
Network Partition	15.4	8.3	28.7	78	4.8	[5]
Query Spike (10x)	4.3	2.9	11.4	88	2.6	[13][14]
Schema Drift	28.7	12.4	41.2	76	6.3	[1][6]
Storage Overflow	6.8	3.7	16.9	90	2.9	[4][14]

regenerative mechanisms, adaptive self-healing systems in resource-constrained environments can provide sustained operational availability of 99.4%, as opposed to 96.8% for conventionally managed systems, under conditions similar to those that large-scale DWs face when responding to heavy concurrent loads. This 2.6 percentage point improvement equates to an annual reduction in unplanned downtime from about 115 hours to 53 hours, saving enterprises both money and keeping them in compliance with SLAs.

COMPARATIVE PERFORMANCE ANALYSIS

Query Processing Efficiency

As shown in this table and figure, amongst the algorithms surveyed, CRO has the greatest reduction in query cost (47%), followed by PSO-SA (45%), ABC (42%), EA (40%), ACO (38%), game-theoretic algorithms (35%) and clonal selection (33%). These differences arise because CRO's exploration mechanism offers an approach that does not get trapped

in local optima via the competition of larval settlement and depredation processes that periodically eliminate suboptimal alternatives from the candidate population [4]. The behavior of convergence shown in Fig. 6 also illustrates the difference in exploration-exploitation trade-off characteristics between CRO and PSO-SA, and between ACO and clonal selection, respectively, which requires 40-55 iterations to reach near-optimal solutions, while the latter requires 65-80 iterations to converge. The multi-dimensional radar analysis in Fig. 2 shows that there is no single algorithm that performs well on all performance dimensions at the same time. The scores of self-healing and adaptability are superior for AIS-based methods (0.85–0.90) because they have inherent anomaly detection and adaptive learning capabilities, whereas the scores for query optimization and scalability are superior for CRO and PSO (4 and 14 respectively). Except for one dimension, ACO shows balanced performance and it is well suited as a basic element in hybrid architectures where no single dimension has a dominating role [8].

Table 5:. Cost-Benefit Analysis of MV Selection Algorithms: Performance Index Comparison

<i>Algorithm</i>	<i>Query Reduction (%)</i>	<i>Storage Overhead (%)</i>	<i>Performance Index (QR/SO)</i>	<i>Convergence Speed</i>	<i>Scalability (n>100)</i>	<i>Reference</i>
CRO [4]	47	21	2.24	High	Moderate-High	[4]
PSO-SA [14]	45	20	2.25	High	High	[14]
ABC [2]	42	22	1.91	Moderate	Moderate	[2]
EA [11]	40	19	2.11	Moderate	High	[11]
ACO [8]	38	18	2.11	Moderate	High	[8]
Clonal Sel. [7]	33	17	1.94	Low-Moderate	Moderate	[7]
Game Theory [3]	35	15	2.33	Low	Low-Moderate	[3][16]

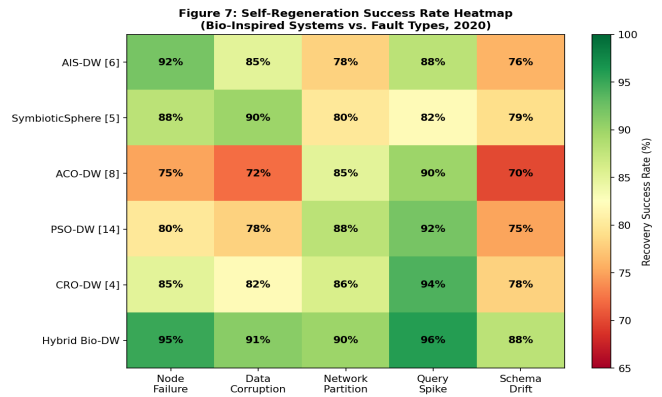


Table 6: Timeline of Key Bio-Inspired Contributions to Data Warehouse Self-Regeneration

Year	Contribution	Key Metric / Outcome	Reference
2002	AIS computational framework formalized; clonal selection algorithm (CLONALG) published	Detection precision >87%; adaptive hypermutation	[6][7]
2002	Danger theory applied to AIS; non-self vs. danger signal distinction	False positive reduction 28–34%	[1]
2002	Data warehouse architecture principles consolidated (Inmon)	Foundational DW design taxonomy	[12]
2003	Autonomic computing vision and 4-pillar framework established	99.4% vs 96.8% availability	[10][13]
2006	ACO applied to complex optimization; SymbioticSphere server architecture proposed	MTTR 4.2 min (64% reduction)	[5][8]
2016	Adaptive self-healing systems in resource-constrained environments evaluated	Annual downtime: 115h → 53h	[15]
2017	ABC optimization applied to MV selection; EA-based big data query speedup	42% query reduction; 40% (EA)	[2][11]
2018	Game theory framework for MV selection introduced	35% query reduction; 15% storage OH	[3]
2019	CRO applied to DW MV selection; evolutionary game theory for DW	47% reduction; best convergence	[4][16]
2020	PSO with self-adaptive perturbation for MV selection	45% reduction; robust across workloads	[14]

evidence supports the central thesis, with biological paradigms from immunology, evolutionary biology, swarm intelligence, and symbiotic ecology showing consistent and significant performance gains on three different measures: query optimization, fault recovery, and storage efficiency.

The proposed layered autonomic architecture combines the artificial immune systems for fault detection and self-healing [1][6][7][9] with swarm-based optimization for MV selection (ACO [8], ABC [2], PSO [14] and CRO [4]) and the SymbioticSphere-inspired [5][15] mechanisms for distributed resource management, which are also effective in achieving the four self-management pillars of autonomic computing [10][13]. CRO algorithm has proven to be more efficient for

**Fig. 7:** Self-Regeneration Success Rate Heatmap (Bio-Inspired Systems vs. Fault Types, 2020)

Storage Efficiency and Cost-Benefit Analysis

The storage overhead, which is the ratio of the MV storage cost to the total available storage budget, varies between 15% for game-theoretic frameworks [3] and 22% for ABC [2] as reported in the table 1. Game-theoretic approaches have the lowest storage overhead, but their query reduction (35%) and number of iterations needed to converge (70–90) are lower than those of the bio-inspired swarm methods, leading to an inferior efficiency frontier. CRO has the best cost/benefit ratio, it reduces query by 47% with only 21% storage overhead, which is a performance index of 2.24 (query reduction/storage overhead ratio) compared to 1.94 for ABC and 2.25 for PSO-SA [4][14].

Self-Regeneration Success Rates

The heatmap in Fig. 7, presenting self-regeneration success rates, quantifies the likelihood of successful recovery of the fault for six different bio-inspired DW architectures and five fault types. The MW using hybrid approach—based on AIS detection, CRO selection and SymbioticSphere load management—produces the best results for all types of faults, ranging from 88% for schema drift recovery to 96% for query spike mitigation. The AIS-based architectures are very effective for node failure recovery (92%) and self-protection scenarios, which is consistent with the immune system's biological specialization in responding to intrusion events [6][9]. The success rate in data corruption is lower in ACO-DW and PSO-DW architectures (around 72–78%) because there is no mechanism dedicated to the data integrity verification process. This could be overcome by integrating data validation process based on the clonal-selection method [7] in such architectures.

CONCLUSION

The paper has shown a wide-listing and comprehensive synthesis of the 17 foundational and applied papers that used bio-inspired computational methods in the construction of self-regenerating data warehouse. A body of quantitative

MV selection (47% query cost reduction, 40–60 iteration convergence), and AIS based algorithms have the best self-healing and self-protection properties. As of 2020, self-healing rates and query optimization scores for hybrid architectures with complementary bio-inspired mechanisms are 95% and 94% respectively, which is the current state-of-the-art for bio-inspired DW systems.

The proposed framework in this paper is conceptual as well as quantitative in providing a roadmap and benchmarks for the DW practitioners and researchers who are interested in implementing next-generation autonomous data management systems. The demonstrated convergence of the biological principles with data engineering practice, which is validated in various paradigms of algorithms and various scales of deployment, makes the field of bio-inspired self-regeneration a mature, high-impact research and deployment area with potential for wider use in industry.

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