

# DDRKAM Reference Manual

## Data-Driven Runge-Kutta and Adams Methods

Shyamal Suhana Chandra

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# 1 Introduction

This manual provides comprehensive documentation for the DDRKAM (Data-Driven Runge-Kutta and Adams Methods) framework. The framework is designed for solving ordinary differential equations (ODEs) with support for traditional and hierarchical data-driven approaches.

The framework includes:

- Euler’s Method (1st order)
- Data-Driven Euler’s Method (DDEuler)
- Runge-Kutta 3rd Order Method (RK3)
- Data-Driven Runge-Kutta 3rd Order (DDRK3)
- Adams Methods (AM)
- Data-Driven Adams Methods (DDAM)

## 2 Euler’s Method

### 2.1 Overview

Euler’s Method is the simplest numerical method for solving ODEs. It is a first-order explicit method with local truncation error  $O(h^2)$ .

### 2.2 Algorithm

$$y_{n+1} = y_n + h \cdot f(t_n, y_n)$$

where  $h$  is the step size,  $f$  is the ODE function, and  $y_n$  is the state at time  $t_n$ .

### 2.3 API Reference

#### 2.3.1 euler\_step

Performs a single integration step using Euler’s method.

```
1 double euler_step(ODEFunction f, double t0, double* y0,  
2                   size_t n, double h, void* params);
```

**Parameters:**

- **f**: Function pointer to the ODE system
- **t0**: Current time
- **y0**: Current state vector (modified in-place)
- **n**: Dimension of the system

### 2.3.2 euler\_solve

Solves an ODE system over a time interval using Euler’s method.

```
1 size_t euler_solve(ODEFunction f, double t0, double t_end,
2                   const double* y0, size_t n, double h,
3                   void* params, double* t_out, double* y_out);
```

## 3 Data-Driven Euler’s Method

### 3.1 Overview

Data-Driven Euler’s Method (DDEuler) extends standard Euler’s method with a hierarchical transformer-inspired architecture that applies adaptiv

### 3.2 Algorithm

$$y_{n+1} = y_n + h \cdot f(t_n, y_n) + h \cdot \alpha \cdot \text{Attention}(y_n)$$

where  $\alpha$  is a learning rate and  $\text{Attention}(y_n)$  is computed through hierarchical transformer layers.

### 3.3 API Reference

#### 3.3.1 hierarchical\_euler\_init

Initializes a Data-Driven Euler solver.

```
1 int hierarchical_euler_init(HierarchicalEulerSolver* solver,
2                             size_t num_layers, size_t state_dim,
3                             size_t hidden_dim);
```

#### 3.3.2 hierarchical\_euler\_step

Performs a single integration step using Data-Driven Euler.

```
1 double hierarchical_euler_step(HierarchicalEulerSolver* solver,
2                                ODEFunction f, double t, double* y,
3                                double h, void* params);
```

#### 3.3.3 hierarchical\_euler\_solve

Solves an ODE system using Data-Driven Euler over a time interval.

```
1 size_t hierarchical_euler_solve(HierarchicalEulerSolver* solver,
2                                 ODEFunction f, double t0, double t_end,
3                                 const double* y0, double h, void* params,
```

## 4 Parallel and Distributed Methods

### 4.1 Overview

All methods support parallel, distributed, concurrent, hierarchical, and stacked execution modes. This enables:

- Multi-threaded execution (OpenMP, pthreads)
- Distributed computing (MPI)
- Concurrent execution of multiple methods
- Hierarchical/stacked architectures
- Enhanced performance and scalability

### 4.2 Parallel Runge-Kutta

#### 4.2.1 `parallel_rk_init`

Initialize parallel RK3 solver.

```
1 int parallel_rk_init(ParallelRKSolver* solver, size_t state_dim,  
2                     size_t num_workers, ParallelMode mode,  
3                     StackedConfig* stacked);
```

#### 4.2.2 `parallel_rk_step`

Perform parallel RK3 step.

```
1 double parallel_rk_step(ParallelRKSolver* solver, ODEFunction f,  
2                       double t, double* y, double h, void* params);
```

#### 4.2.3 `stacked_rk_step`

Perform stacked/hierarchical RK3 step.

```
1 double stacked_rk_step(ParallelRKSolver* solver, ODEFunction f,  
2                       double t, double* y, double h, void* params);
```

#### 4.2.4 `concurrent_rk_execute`

Execute multiple RK3 instances concurrently.

```
1 int concurrent_rk_execute(ParallelRKSolver* solvers[], size_t num_solvers,  
2                          ODEFunction f, double t, const double* y, double h,  
3                          int num_threads, double dt, double h_min);
```

## 5 Real-Time, Online, and Dynamic Methods

### 5.1 Real-Time Methods

Real-time methods process streaming data with minimal latency.

#### 5.1.1 `realtime_rk_init`

Initialize real-time RK3 solver.

```
1 int realtime_rk_init(RealtimeRKSolver* solver, size_t state_dim,  
2                     double step_size, DataCallback callback,  
3                     void* callback_data);
```

#### 5.1.2 `realtime_rk_step`

Perform real-time RK3 step with streaming support.

```
1 double realtime_rk_step(RealtimeRKSolver* solver, ODEFunction f,  
2                     double t, double* y, double h, void* params);
```

### 5.2 Online Methods

Online methods adapt to incoming data with incremental learning.

#### 5.2.1 `online_rk_init`

Initialize online RK3 solver.

```
1 int online_rk_init(OnlineRKSolver* solver, size_t state_dim,  
2                     double initial_step_size, double learning_rate);
```

#### 5.2.2 `online_rk_step`

Perform online RK3 step with adaptive step size.

```
1 double online_rk_step(OnlineRKSolver* solver, ODEFunction f,  
2                     double t, double* y, void* params);
```

### 5.3 Dynamic Methods

Dynamic methods provide fully adaptive execution.

#### 5.3.1 `dynamic_rk_init`

### 5.3.2 dynamic\_rk\_step

Perform dynamic RK3 step with adaptive parameters.

```
1 double dynamic_rk_step(DynamicRKSolver* solver, ODEFunction f,  
2                       double t, double* y, void* params);
```

## 6 Nonlinear Programming Solvers

### 6.1 Karmarkar's Algorithm

Karmarkar's Algorithm is a polynomial-time interior point method for linear programming. It provides guaranteed polynomial-time convergence for

#### 6.1.1 karmarkar\_solver\_init

Initialize Karmarkar solver.

```
1 int karmarkar_solver_init(KarmarkarSolver* solver, size_t state_dim,  
2                          ADAMSolverType type, double alpha, double beta,  
3                          double mu, double epsilon, const double* c,  
4                          const double** A, const double* b,  
5                          size_t num_constraints);
```

#### 6.1.2 karmarkar\_ode\_solve

Solve ODE using Karmarkar's algorithm.

```
1 int karmarkar_ode_solve(KarmarkarSolver* solver, ODEFunction f,  
2                       double t0, double t_end, const double* y0,  
3                       void* params, double* y_out);
```

### 6.2 Nonlinear ODE Solver

#### 6.2.1 nonlinear\_ode\_init

Initialize nonlinear ODE solver using NLP methods.

```
1 int nonlinear_ode_init(NonlinearODESolver* solver, size_t state_dim,  
2                      NLPSolverType solver_type, ObjectiveFunction objective,  
3                      ConstraintFunction constraints, void* params);
```

#### 6.2.2 nonlinear\_ode\_solve

Solve ODE using nonlinear programming.



## 6.3 Nonlinear PDE Solver

### 6.3.1 nonlinear\_pde\_init

Initialize nonlinear PDE solver.

```
1 int nonlinear_pde_init(NonlinearPDESolver* solver, size_t spatial_dim,  
2                       const size_t* grid_size, NLP SolverType solver_type,  
3                       PDEFunction pde_func, void* params);
```

### 6.3.2 nonlinear\_pde\_solve

Solve PDE using nonlinear programming.

```
1 int nonlinear_pde_solve(NonlinearPDESolver* solver, double t0, double t_end,  
2                       const double* u0, double* u_out);
```

## 7 Additional Distributed, Data-Driven, Online, Real-Time Solvers

### 7.1 Distributed Data-Driven Solver

Combines distributed computing with data-driven methods.

### 7.2 Online Data-Driven Solver

Combines online learning with data-driven methods.

### 7.3 Real-Time Data-Driven Solver

Combines real-time processing with data-driven methods.

### 7.4 Distributed Online Solver

Combines distributed computing with online learning.

### 7.5 Distributed Real-Time Solver

Combines distributed computing with real-time processing.

## 8 Runge-Kutta 3rd Order Method

### 8.1 Overview

## 8.2 API Reference

### 8.2.1 rk3\_step

Performs a single integration step using RK3.

```
1 double rk3_step(ODEFunction f, double t0, double* y0,  
2               size_t n, double h, void* params);
```

#### Parameters:

- f: Function pointer to the ODE system
- t0: Current time
- y0: Current state vector (modified in-place)
- n: Dimension of the system
- h: Step size
- params: User-defined parameters

**Returns:** New time value ( $t_0 + h$ )

### 8.2.2 rk3\_solve

Solves an ODE system over a time interval.

```
1 size_t rk3_solve(ODEFunction f, double t0, double t_end,  
2               const double* y0, size_t n, double h,  
3               void* params, double* t_out, double* y_out);
```

#### Parameters:

- f: Function pointer to the ODE system
- t0: Initial time
- t\_end: Final time
- y0: Initial state vector
- n: Dimension of the system
- h: Step size
- params: User-defined parameters
- t\_out: Output time array (allocated by caller)

## 8.3 Example

```
1 void lorenz(double t, const double* y, double* dydt, void* params) {
2     double* p = (double*)params;
3     double sigma = p[0], rho = p[1], beta = p[2];
4     dydt[0] = sigma * (y[1] - y[0]);
5     dydt[1] = y[0] * (rho - y[2]) - y[1];
6     dydt[2] = y[0] * y[1] - beta * y[2];
7 }
8
9 double params[3] = {10.0, 28.0, 8.0/3.0};
10 double y0[3] = {1.0, 1.0, 1.0};
11 double t_out[100];
12 double y_out[300];
13 size_t steps = rk3_solve(lorenz, 0.0, 1.0, y0, 3, 0.01,
14                          params, t_out, y_out);
```

## 9 Adams Methods

### 9.1 Adams-Bashforth 3rd Order

Predictor step for multi-step integration.

```
1 void adams_bashforth3(ODEFunction f, const double* t,
2                          const double* y, size_t n, double h,
3                          void* params, double* y_pred);
```

### 9.2 Adams-Moulton 3rd Order

Corrector step for multi-step integration.

```
1 void adams_moulton3(ODEFunction f, const double* t,
2                      const double* y, size_t n, double h,
3                      void* params, const double* y_pred,
4                      double* y_corr);
```

## 10 Hierarchical Runge-Kutta Method

### 10.1 Overview

The hierarchical RK method uses a transformer-like architecture with multiple processing layers and attention mechanisms.

### 10.2 API Reference

```

1  int hierarchical_rk_init(HierarchicalRKSolver* solver,
2                          size_t num_layers, size_t state_dim,
3                          size_t hidden_dim);

```

**Returns:** 0 on success, -1 on failure

### 10.2.2 hierarchical\_rk\_free

Frees resources allocated by the solver.

```

1  void hierarchical_rk_free(HierarchicalRKSolver* solver);

```

### 10.2.3 hierarchical\_rk\_solve

Solves an ODE using the hierarchical method.

```

1  size_t hierarchical_rk_solve(HierarchicalRKSolver* solver,
2                              ODEFunction f, double t0, double t_end,
3                              const double* y0, double h, void* params,
4                              double* t_out, double* y_out);

```

## 11 Objective-C Framework

### 11.1 DDRKAMSolver

Main solver class for Objective-C applications.

```

1  DDRKAMSolver* solver = [[DDRKAMSolver alloc]
2                          initWithDimension:3];
3  NSDictionary* result = [solver solveWithFunction:^(double t,
4                                                      const double* y,
5                                                      double* dydt,
6                                                      void* params) {
7      // ODE definition
8  } startTime:0.0 endTime:1.0
9  initialState:@[@1.0, @1.0, @1.0]
10 stepSize:0.01 params:NULL];

```

### 11.2 DDRKAMVisualizer

Visualization component for plotting solutions.

```

1  DDRKAMVisualizer* viz = [[DDRKAMVisualizer alloc] init];
2  UIView* view = [viz createVisualizationViewWithTime:timeArray
3                  state:stateArray
4                  dimension:3];

```

## 11.3 DDRKAMHierarchicalSolver

Hierarchical solver for Objective-C.

```
1 DDRKAMHierarchicalSolver* solver =
2     [[DDRKAMHierarchicalSolver alloc]
3         initWithDimension:3 numLayers:4 hiddenDim:32];
```

## 12 Map/Reduce Framework

### 12.1 Overview

The Map/Reduce framework provides distributed ODE solving on commodity hardware with fault tolerance through redundancy. It partitions the processes derivatives in parallel, and aggregates results through reducer nodes.

### 12.2 API Reference

#### 12.2.1 mapreduce\_ode\_init

Initializes a Map/Reduce ODE solver.

```
1 int mapreduce_ode_init(MapReduceODESolver* solver,
2                       size_t state_dim,
3                       const MapReduceConfig* config);
```

**Parameters:**

- **solver:** Pointer to Map/Reduce solver structure
- **state\_dim:** Dimension of the ODE system
- **config:** Configuration structure with mapper/reducer counts, redundancy settings, etc.

**Returns:** 0 on success, -1 on failure

#### 12.2.2 mapreduce\_ode\_solve

Solves an ODE system using Map/Reduce framework.

```
1 int mapreduce_ode_solve(MapReduceODESolver* solver,
2                       ODEFunction f,
3                       double t0, double t_end,
4                       const double* y0,
5                       double h, void* params,
6                       double* y_out);
```

**Parameters:**

- t0, t\_end: Time interval
- y0: Initial state
- h: Step size
- params: User-defined parameters
- y\_out: Output state

**Returns:** 0 on success, -1 on failure

### 12.2.3 mapreduce\_estimate\_cost

Estimates the computational cost for Map/Reduce execution.

```
1 double mapreduce_estimate_cost(const MapReduceODESolver* solver,
2                               double* compute_hours,
3                               double* network_cost);
```

## 12.3 Example

```
1 #include "mapreduce_solvers.h"
2
3 MapReduceODESolver solver;
4 MapReduceConfig config = {
5     .num_mappers = 4,
6     .num_reducers = 2,
7     .chunk_size = 100,
8     .enable_redundancy = 1,
9     .redundancy_factor = 3,
10    .use_commodity_hardware = 1,
11    .network_bandwidth = 100.0,
12    .compute_cost_per_hour = 0.10
13 };
14
15 mapreduce_ode_init(&solver, 1000, &config);
16
17 double y0[1000] = {1.0, ...};
18 double y_out[1000];
19 mapreduce_ode_solve(&solver, my_ode, 0.0, 1.0, y0, 0.01, NULL, y_out);
20
21 double cost = mapreduce_estimate_cost(&solver, NULL, NULL);
22 mapreduce_ode_free(&solver);
```

# 13 Apache Spark Framework

## 13.1 Overview

The Apache Spark framework provides distributed ODE solving using Resilient Distributed Datasets (RDDs) for fault-tolerant computation. Spark also supports iterative algorithms through RDD caching and lineage-based recovery.

## 13.2 API Reference

### 13.2.1 spark\_ode\_init

Initializes a Spark ODE solver.

```
1 int spark_ode_init(SparkODESolver* solver,
2                   size_t state_dim,
3                   const SparkConfig* config);
```

**Parameters:**

- `solver`: Pointer to Spark solver structure
- `state_dim`: Dimension of the ODE system
- `config`: Configuration structure with executor counts, caching settings, etc.

**Returns:** 0 on success, -1 on failure

### 13.2.2 spark\_ode\_solve

Solves an ODE system using Spark framework.

```
1 int spark_ode_solve(SparkODESolver* solver,
2                   ODEFunction f,
3                   double t0, double t_end,
4                   const double* y0,
5                   double h, void* params,
6                   double* y_out);
```

**Parameters:**

- `solver`: Initialized Spark solver
- `f`: ODE function pointer
- `t0`, `t_end`: Time interval
- `y0`: Initial state
- `h`: Step size

### 13.2.3 spark\_estimate\_cost

Estimates the computational cost for Spark execution.

```
1 double spark_estimate_cost(const SparkODESolver* solver,
2                             double* compute_hours,
3                             double* network_cost,
4                             double* storage_cost);
```

## 13.3 Example

```
1 #include "spark_solvers.h"
2
3 SparkODESolver solver;
4 SparkConfig config = {
5     .num_executors = 4,
6     .cores_per_executor = 2,
7     .memory_per_executor = 2048,
8     .num_partitions = 8,
9     .enable_caching = 1,
10    .enable_checkpointing = 1,
11    .checkpoint_interval = 1.0,
12    .use_commodity_hardware = 1,
13    .network_bandwidth = 100.0,
14    .compute_cost_per_hour = 0.10,
15    .enable_dynamic_allocation = 1
16 };
17
18 spark_ode_init(&solver, 1000, &config);
19
20 double y0[1000] = {1.0, ...};
21 double y_out[1000];
22 spark_ode_solve(&solver, my_ode, 0.0, 1.0, y0, 0.01, NULL, y_out);
23
24 double cost = spark_estimate_cost(&solver, NULL, NULL, NULL);
25 spark_ode_free(&solver);
```

## 14 Non-Orthodox Architectures

### 14.1 Micro-Gas Jet Circuit

Micro-gas jet circuits use fluid dynamics for computation. See `nonorthodox_architectures.h` for API.



### 14.3 ACE (Turing)

Turing's stored-program computer architecture implementation.

### 14.4 Systolic Array

Regular array of processing elements with local communication.

### 14.5 TPU (Patterson)

Google TPU architecture for matrix acceleration.

### 14.6 GPU Architectures

Support for CUDA, Metal, Vulkan, and AMD GPU acceleration.

### 14.7 Spiralizer with Chord Algorithm (Chandra, Shyamal)

Spiralizer architecture combining Chord distributed hash tables with Robert Morris collision hashing (MIT) and spiral traversal patterns.

**API:**

```
1 SpiralizerChordConfig config = {
2     .num_nodes = 256,
3     .finger_table_size = 8,
4     .hash_table_size = 1024,
5     .enable_morris_hashing = 1,
6     .enable_spiral_traversal = 1
7 };
8 SpiralizerChordSolver solver;
9 spiralizer_chord_ode_init(&solver, n, &config);
10 spiralizer_chord_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
11 spiralizer_chord_ode_free(&solver);
```

### 14.8 Lattice Architecture (Waterfront variation - Chandra, Shyamal)

Variation of Turing's Waterfront architecture, presented by USC alum from HP Labs at MIT event online at Strata. Multi-dimensional lattice with

**API:**

```
1 LatticeWaterfrontConfig config = {
2     .lattice_dimensions = 4,
3     .nodes_per_dimension = 16,
4     .waterfront_size = 256,
5     .enable_waterfront_buffering = 1,
6     .enable_lattice_routing = 1
```

```
11 lattice_waterfront_ode_free(&solver);
```

## 14.9 Standard Parallel Computing Architectures

### MPI (Message Passing Interface):

```
1 MPIConfig config = {
2     .num_processes = 8,
3     .process_rank = 0,
4     .communication_buffer_size = 1024,
5     .enable_collective_ops = 1
6 };
7 MPISolver solver;
8 mpi_ode_init(&solver, n, &config);
9 mpi_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
10 mpi_ode_free(&solver);
```

### OpenMP (Open Multi-Processing):

```
1 OpenMPConfig config = {
2     .num_threads = 8,
3     .chunk_size = 64,
4     .schedule_type = 1, // dynamic
5     .enable_affinity = 1
6 };
7 OpenMPSolver solver;
8 openmp_ode_init(&solver, n, &config);
9 openmp_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
10 openmp_ode_free(&solver);
```

### Pthreads (POSIX Threads):

```
1 PthreadsConfig config = {
2     .num_threads = 8,
3     .enable_work_stealing = 1,
4     .enable_barrier_sync = 1
5 };
6 PthreadsSolver solver;
7 pthreads_ode_init(&solver, n, &config);
8 pthreads_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
9 pthreads_ode_free(&solver);
```

## 14.10 Specialized Hardware Architectures

### FPGA AWS F1 (Xilinx UltraScale+):

```

5     .pcie_bandwidth = 16,    // GB/s
6     .enable_hls_acceleration = 1
7 };
8 FPGAAWSF1Solver solver;
9 fpga_aws_f1_ode_init(&solver, n, &config);
10 fpga_aws_f1_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
11 fpga_aws_f1_ode_free(&solver);

```

#### TilePU Sunway (SW26010):

```

1 TilePUSunwayConfig config = {
2     .num_core_groups = 4,
3     .cores_per_group = 64,
4     .num_management_cores = 4,
5     .enable_dma = 1,
6     .enable_register_communication = 1
7 };
8 TilePUSunwaySolver solver;
9 tilepu_sunway_ode_init(&solver, n, &config);
10 tilepu_sunway_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
11 tilepu_sunway_ode_free(&solver);

```

#### Coprocessor Intel Xeon Phi:

```

1 CoprocessorXeonPhiConfig config = {
2     .num_cores = 72,
3     .num_threads_per_core = 4,
4     .high_bandwidth_memory = 16,    // GB
5     .enable_wide_vector = 1,    // 512-bit
6     .enable_mic_architecture = 1
7 };
8 CoprocessorXeonPhiSolver solver;
9 coprocessor_xeon_phi_ode_init(&solver, n, &config);
10 coprocessor_xeon_phi_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
11 coprocessor_xeon_phi_ode_free(&solver);

```

## 14.11 Additional Architectures

See `nonorthodox_architectures.h` for:

- Standard Parallel Computing: MPI (Message Passing Interface), OpenMP (Open Multi-Processing), Pthreads (POSIX Threads)
- GPGPU (General-Purpose GPU) for platform-agnostic GPU computing
- Vector Processor architecture for SIMD data-parallel operations

- Specialized Processing Units: TilePU Mellanox (Tile-GX72), TilePU Sunway (SW26010), DPU Microsoft (biological computation), MFPU (Morphological Processing Unit), LPU Lightmatter (photonic computing)
- AsAP (Asynchronous Array of Simple Processors) - UC Davis architecture
- Coprocessor: Intel Xeon Phi many-core coprocessor with wide vector units
- Massively-Threaded (Korf) - Frontier search with massive threading
- STARR (Chandra et al.) - Semantic memory architecture - <https://github.com/shyamalschandra/STARR>
- TrueNorth (IBM), Loihi (Intel), BrainChips - Neuromorphic architectures
- Racetrack (Parkin), Phase Change Memory (IBM)
- Lyric (MIT), HW Bayesian Networks (Chandra)
- Semantic Lexographic Binary Search (Chandra & Chandra)
- Kernelized SPS Binary Search (Chandra, Shyamal)
- Multiple-Search Representation Tree Algorithm

## 14.12 Multiple-Search Representation Tree Algorithm

Uses multiple search strategies (BFS, DFS, A\*, Best-First) with tree and graph state representations.

**API:**

```

1 MultipleSearchTreeConfig config = {
2     .max_tree_depth = 100,
3     .max_nodes = 10000,
4     .num_search_strategies = 4,
5     .enable_bfs = 1,
6     .enable_dfs = 1,
7     .enable_astar = 1,
8     .enable_best_first = 1,
9     .heuristic_weight = 1.0
10 };
11 MultipleSearchTreeSolver solver;
12 multiple_search_tree_ode_init(&solver, n, &config);
13 multiple_search_tree_ode_solve(&solver, f, t0, t_end, y0, h, params, y_out);
14 multiple_search_tree_ode_free(&solver);

```

## 15 Platform Support

- macOS 10.13+

## 16 Copyright

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