Darwin Optimization User Manual

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I. ACKNOWLEDGEMENT

Darwin optimization has been incrementally developed and improved since 2009. A few research interns worked on the project. I'd like to acknowledge the contribution made by Swaroop Butala, Qiben Wang, Tian Mi and Yuan Song who have worked on the project from 2009 to 2012 respectively. The project has been under the direction and supervision of Zheng Yi Wu at Bentley Systems, Incorporated, Watertown CT office. It is much appreciated that you cite our work in the project, presentation and publication for using the framework.

Citation can be made as follows.
Wu, Z. Y., Wang, Q, Butala, S., Mi T. and Song Y. (2012). "Darwin Optimization User Manual." Bentley Systems, Incorporated, Watertown, CT 06795, USA.

II. EXECUTIVE SUMMARY

Darwin optimization framework is designed and developed as the general tool for rapid implementation of optimization applications. The framework encapsulates the search algorithms, parallel computing/evaluating possible solutions and constraint handling methods. The core search engines are generalized from three Bentley products Darwin Calibrator and Darwin Designer and Darwin Scheduler as embedded and released as optimization modeling tools of Bentley Water Solution. Darwin framework allows parallel optimization on a single many-core machine and a cluster of many-core machines. It enables user to solve single and multi objective optimization problems with linear, nonlinear, inequity and equity constraints.

The framework relives developers from implementing and integrating the optimization algorithm with an analysis solver, and thus allows developers to focus on defining, formulating and implementing the domain applications. The framework works with the optimization application that is formulated with objective function(s) and constraints. They are implemented in a class library project, which is built as an independent DLL dynamically loaded at run time. Therefore, Darwin optimization framework enables rapid prototype and implementation of optimization projects.

Table of Contents

1. INTRODUCTION

This document is a detailed user or developer manual on how to use Darwin framework to solve an optimization problem. It elaborates on how to apply Darwin framework, specifically on what input files are needed, how to link those files to Darwin framework, how to run Darwin optimization, and how to check results.

The manual covers the essential steps for using Darwin framework as follows.

1) Define optimization decision variables
2) Implement Darwin fitness application (objective and constraint functions) as Dynamically Linked Library (DLL)
3) Prepare the configuration file in XML format to specify DLL file's path, namespace, class name, and fitness function name
4) Prepare Darwin parameters for Genetic Algorithm optimization
5) Perform Darwin optimization runs (sequential and parallel)
6) Examples in C# and C++ for single and multiple objective optimization

2. DAWRIN FRAMEWORK OVERVIEW

In general, solving an optimization problem is to search for a set of optimal or near-optimal values of decision variables to minimize and/or maximize the predefined objective function(s) while meeting the constraints. During the optimization process, each decision variable is taking the values within its prescribed range with specified increment, and the objective function (or multiple objective functions) and constraint functions are evaluated for each possible solution.

Darwin optimization framework is developed as an effective and scalable tool to solve highly generalized optimization problems with Genetic Algorithm (GA). It has the following features including:

1) Solve for linear and nonlinear optimization problems;
2) Handle linear, nonlinear equality and inequality constraints;
3) Solve Single and multiple objective optimization problems;
4) Enable parallel optimization on a single many-core machine and a cluster of many-core machines;
5) Enable quick optimization implementation by decoupling optimization solvers from optimization applications;
6) Provide GUI for running Darwin optimization, it can also be embedded in an application;

7) Offer dynamic runtime of optimization convergence rate for both single and multi objective optimization runs.

2.1. Optimization Problem Formulation

Before applying Darwin optimization framework, it is expected that users or developers should carefully analyze their problem and formulate the optimization problem. This includes:

1) Definition of decision variables. For each variable, the lower and upper bounds must be specified as the minimum and maximum values for the variable.
2) Definition of objective functions. It is objective functions that quantify the optimality of a solution. There can be single or multiple objective functions. In case multiple objective functions are required for evaluating each solution, they must be conflict objectives. Otherwise simply add them to one single objective function.
3) Definition of constraints. It is constraints that govern the feasibility of a solution. All the constraints will be evaluated for each possible solution during optimization process. If one constraint is violated, the amount of violation will be used to deteriorate the optimality of the solution.

In general, an optimization problem can be represented or formulated as follows.

Search for: $X = (x_1, x_2, x_3, \dots x_N)$
Minimize: $F_1(X)$
and/or
Minimize: $F_2(X)$
Subject to: $G_i(X) \geq 0$
$H_j(X) = 0$
$\underline{x}_k \leq x_k \leq \overline{x}_k,\ x_k \in \{x_{k1}, \dots, x_{km}\}, k = 1, \dots, N$

In applying Darwin optimization framework, decision variables x_k (k = 1, 2, 3, …, *N*), the upper limit $\overline{x}_k$ and lower limit $\underline{x}_k$ together with the increment for each decision variable are specified in **decision file**. The objective function(s) $F_1(X)$, $F_2(X)$, constraints $G_i(X)$ and $H_j(X)$ are implemented in a user defined **Darwin application**, a dynamically linked library (DLL). The optimization problem is solved by using genetic algorithms (GA). Two genetic algorithms, namely simple GA and fast messy GA, have been implemented in Darwin optimization engines.

2.2. Constraint Handling

Two methods including penalty method and violation-based selection have been implemented in Darwin optimization for handling constraints.

1) Penalty method. For each solution, every constraint is evaluated in user defined fitness DLL. Constraint violations are calculated and passed back to Darwin. A penalty is obtained by multiplying the sum of the violations with the specified penalty factor. In case of single objective optimization using GA. The final fitness value is the sum of the objective value and the penalty. For the solution that meets all the constraints, the penalty is zero, otherwise a positive term.

2) Violation-based selection. This method is implemented in fast messy GA. In this approach, no penalty factor is required. The constraints are handled by the violation. The following rules are used for GA selection when two solutions are selected for producing new solutions (offspring).
    a. If they are feasible (meeting all constraints), the solution with better fitness value is selected.
    b. If they are infeasible, the solution with smaller violation is selected.
    c. If one is feasible and the other is infeasible, the feasible solution is selected.

3. INSTALLATION AND QUICK START

3.1. Prerequisite

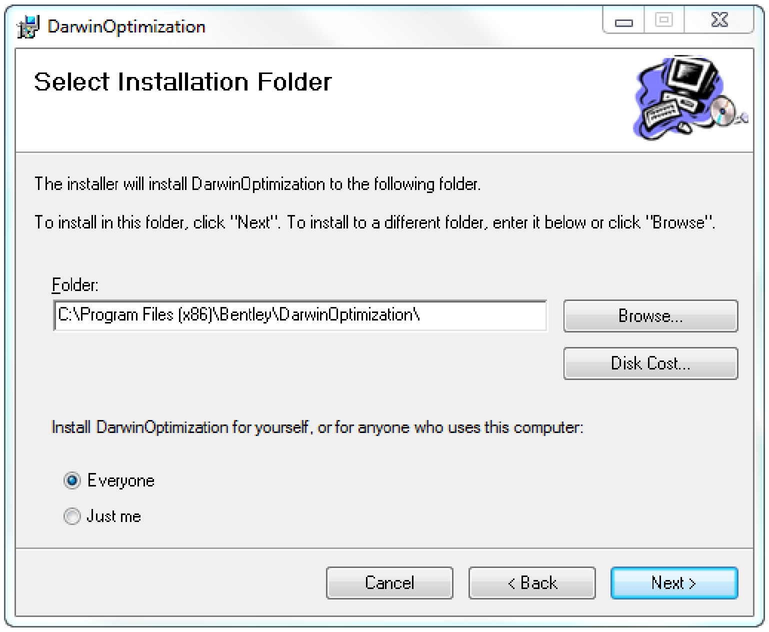
Darwin optimization framework has been developed by using Microsoft message passing interface (MS-MPI). In order to run Darwin, Microsoft MPI library must be installed. It can be downloaded at the following link.

http://www.microsoft.com/download/en/details.aspx?id=14737

Please download and install the corresponding component for your system of 32-bit or 64-bit machine.

3.2. Installation

To facilitate the application of Darwin application, an installation file is created for users for quick installation. Click on the setup file **Bentley.Darwin.Setup.exe** and simply follow the on-screen steps to install Darwin Optimization version 0.91, which include library files, executable files, configuration file and parameter files.


DarwinOptimization

Select Installation Folder

The installer will install DarwinOptimization to the following folder.

To install in this folder, click "Next". To install to a different folder, enter it below or click "Browse".

Folder: C:\Program Files (x86)\Bentley\DarwinOptimization\

Install DarwinOptimization for yourself, or for anyone who uses this computer:

[✓ Everyone]

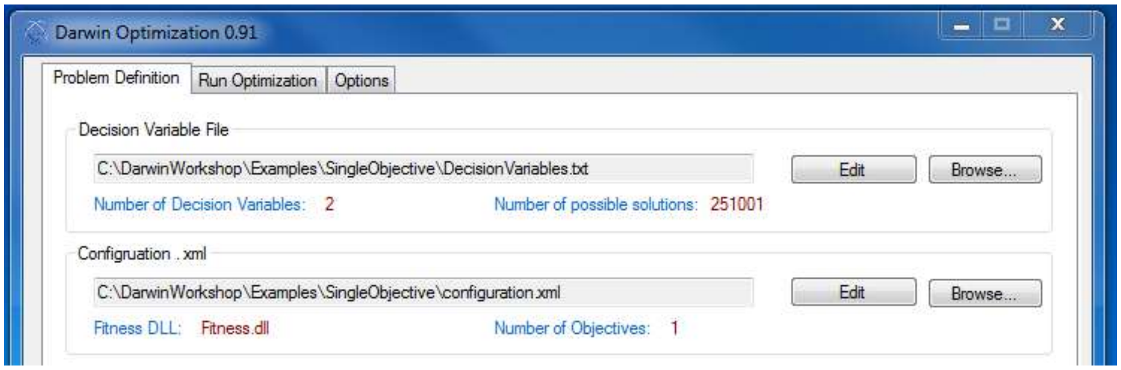
Just me

Darwin optimization framework can be installed at any specified folder. For easy reference, let's assume it be installed at the default folder **C:\Program Files (x86)\Bentley\DarwinOptimization\**, as shown above. After successful installation, Darwin Optimization icon will be placed on the desktop.

3.3. Make a Quick Run

After successfully installing the prerequisite component and Darwin, follow the steps below to make a quick run of Darwin with the installed example.

1) Open Windows Explorer, make a new folder "**C:\DarwinWorkshop**".
2) Copy **Examples** folder from **C:\Program Files (x86)\Bentley\DarwinOptimization** to **C:\DarwinWorkshop.**
3) Copy **Configuration.xml** from **C:\Program Files (x86)\Bentley\DarwinOptimization\bin** to **C:\DarwinWorkshop\Examples\SingleObjective**
4) Double click on Darwin Optimization icon on the desktop, it will open Darwin Optimization 0.91 dialog form, which contains three Tabs **Problem Definition**, **Run Optimization** and **Options** on the top.
5) Click on **Problem Definition** Tab, within Decision Variable File section, click on **Browse** button to browse to the following folder: **C:\DarwinWorkshop\Examples\SingleObjective**
6) Load the file **DecisionVariables.txt** from the folder as shown below.



Decision Variable File

C:\DarwinWorkshop\Examples\SingleObjective\DecisionVariables.txt

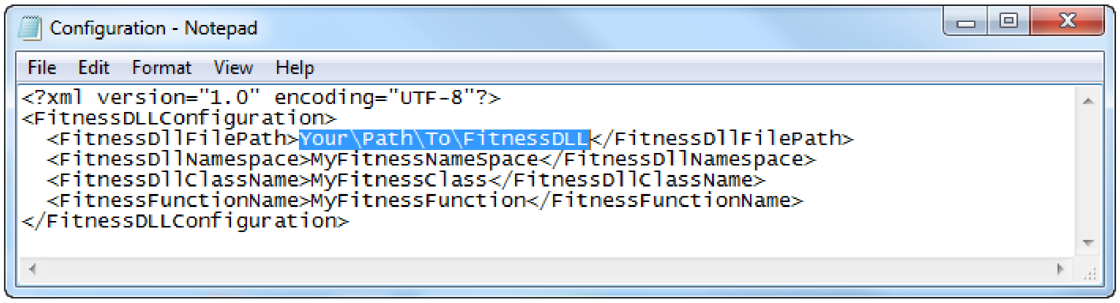
Number of Decision Variables: 2   Number of possible solutions: 251001

Configruation . xml

C:\DarwinWorkshop\Examples\SingleObjective\configuration.xml

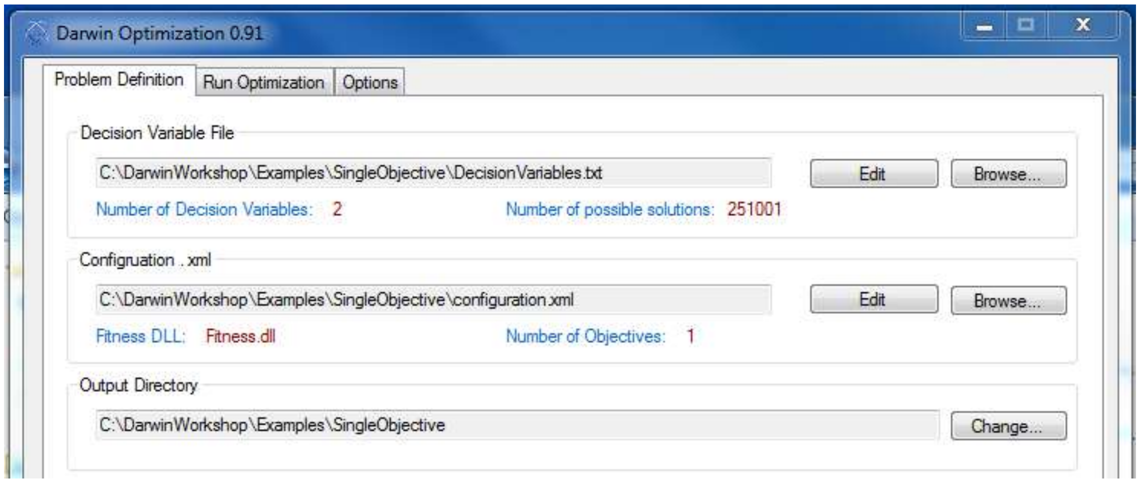
Fitness DLL: Fitness.dll   Number of Objectives: 1

7) Within Configuration section, Click on **Edit** button, it opens the configuration file **Configuration.xml** in Notepad as follows.



```
<?xml version="1.0" encoding="UTF-8"?>
<FitnessDLLConfiguration>
  <FitnessDllFilePath>Your\Path\To\FitnessDLL</FitnessDllFilePath>
  <FitnessDllNamespace>MyFitnessNameSpace</FitnessDllNamespace>
  <FitnessDllClassName>MyFitnessClass</FitnessDllClassName>
  <FitnessFunctionName>MyFitnessFunction</FitnessFunctionName>
</FitnessDLLConfiguration>
```

8) Replace "**Your\Path\To\FitnessDLL**" as highlighted with "**C:\DarwinWorkshop\Examples\SingleObjective\Fitness.dll**"
9) Save the configuration file and close the file.
10) By default, Output Directory is set to your local user folder. To change it, click on Change button within Output Directory section, it will allow you to change the output folder as desired, e.g. **C:\DarwinWorkshop\Examples\SingleObjective**, as shown below.



Decision Variable File

C:\DarwinWorkshop\Examples\SingleObjective\DecisionVariables.txt

Number of Decision Variables: 2   Number of possible solutions: 251001

Configruation . xml

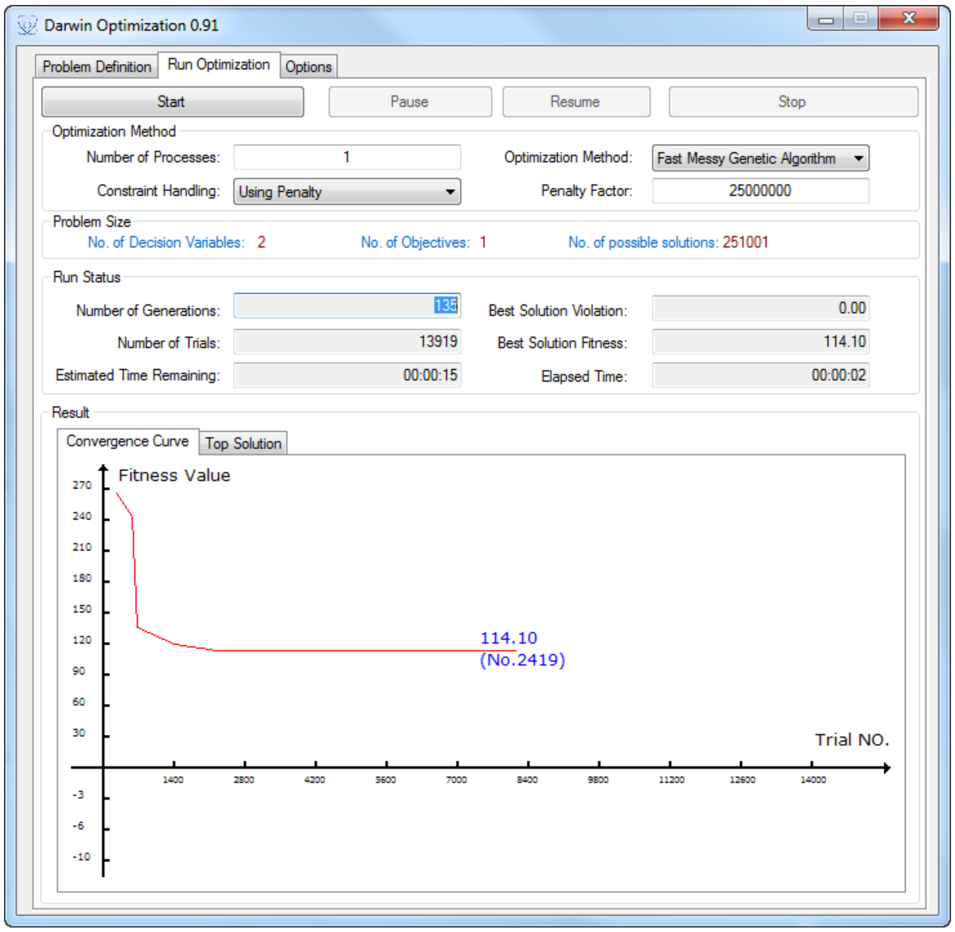
C:\DarwinWorkshop\Examples\SingleObjective\configuration.xml

Fitness DLL: Fitness.dll   Number of Objectives: 1

Output Directory

C:\DarwinWorkshop\Examples\SingleObjective

11) Click on **Run Optimization** tab, and then simply click on **Start** button to make a run. At the run time, you can pause by click on Pause button, resume the run by clicking on Resume button, or stop the run by clicking on Stop button.



Optimization Method
Number of Processes: 1
Optimization Method: Fast Messy Genetic Algorithm
Constraint Handling: Using Penalty
Penalty Factor: 25000000

Problem Size
No. of Decision Variables: 2
No. of Objectives: 1
No. of possible solutions: 251001

Run Status
Number of Generations: 135
Best Solution Violation: 0.00
Number of Trials: 13919
Best Solution Fitness: 114.10
Estimated Time Remaining: 00:00:15
Elapsed Time: 00:00:02

Result

4. IMPLEMENT DARWIN APPLICATION

The following numerical optimization problem is used as an example for implementing Darwin application.

Minimize: O_1: $10X_0+11X_1$

Subject to: C_1: $X_0 + X_1 >= 11$

C_2: $X_0 - X_1 <= 5$

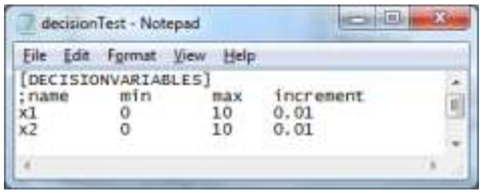
C_3: $7 X_0 + 12 X_1 >= 35$

C_4: $0 <= X_0, X_1 <= 10$

Decision file (decisionTest.txt) is created to define the options for the optimization variables as follows.

4.1. Define Decision Variables

Optimization variables are specified in a text file. It follows the format as in figure below.



```
[DECISIONVARIABLES]
;name       min         max     increment
x1          0           10      0.01
x2          0           10      0.01
```

Definition of optimization variables

Decision variables are defined with a header [DECISIONVARIABLES] and followed by minimum, maximum and increment for each variable. Darwin optimization is to search for the near-optimal value in between the upper and lower limits with the specified increment.

The file can be named as **Decision.txt** or any desired name. It is suggested that the file be saved in the same folder as Output Directory.

The primary task for developing and prototyping Darwin optimization application is to implement the objective and constraint functions. The implementation can proceed with C# and C++.

4.2. Steps for Creating Darwin Application with C#

1) In Microsoft Visual Studio, **File** -> **New** -> **Project**

2) In **Visual C#**, under **Windows**, choose “**Class Library**”, specify **Name** e.g. “FitnessTest” (this will be the DLL file name after building later on), **Location**, and **Solution Name**, click **OK**.

3) Fitness function must be specified as the prototype as follows.

```
int MyFitnessFuntion(ArrayList, ArrayList, ArrayList, ArrayList, int, bool)
```

4) Specify the namespace (e.g. MyFitnessNameSpace), class (e.g. MyFitnessClass) and fitness function name (e.g. MyFitnessFunction). Your project source file contains as follows.

```
using System;
using System.Collections;

namespace MyFitnessNameSpace
```

```
{
    public class MyFitnessClass
    {
        #region Fitness Calculation method

        public int MyFitnessFunction(ArrayList x_ArrayList, ArrayList f_ArrayList,
ArrayList g_ArrayList, ArrayList h_ArrayList, int rank, bool terminated)
        {
            //TODO your implementation; example code is provided in section 6.1
           //Alternatively, the code in section 6.1 or from file FitnessCodes.cs can be
           //copied and pasted here


            return 1;
        }
        #endregion
    }
}
```

5) Implement fitness function as follows (Please see the sample code Section 6).

   a. Definition of fitness function

   Following the example is provided with Darwin optimization framework, the definition of the fitness function is as follows.

   ```
   public int MyFitnessFunction(ArrayList x_ArrayList, ArrayList
   f_ArrayList, ArrayList g_ArrayList, ArrayList h_ArrayList, int
   rank, bool terminated)
   ```

   b. Parameters and return value of fitness function

   `ArrayList x_ArrayList`: current solution (decision variable values) passed from Darwin Framework. The size of `x_ArrayList` is the same as the number of variables in the decision file.

   `ArrayList f_ArrayList`: store objective function value(s) to be calculated for the current solution stored in `x_ArrayList`. After objective value is calculated for the solution, it is added to `f_ArrayList`, which returns it to Darwin Framework. The size of the `f_ArrayList` is the same as the number of objective function(s).

   `ArrayList g_ArrayList`: store the violation of inequality constraint functions, which are calculated for the current solution (decision values) in x`_ArrayList`. The violation is added to `g_ArrayList`, which returns the violation to Darwin Framework. The size of the `g_ArrayList` is the same as the number of inequality constraint functions. Value of 0 indicates the constraint is satisfied. The larger the values, the worse violated the current trial solution is.

   `ArrayList h_ArrayList`: store the violation of equality constraint functions, which are calculated for the current solution in x`_ArrayList`. The violation is added to `h_ArrayList`, which return the violation to Darwin Framework.

`int rank`: a parameter of processor rank when running parallel optimizaiton. Usually not used in this function.

`bool terminated`: check whether or not the GA engine is terminated. Usually it is used as follows in the fitness function body.

```
    if (terminated)
    {
        Console.WriteLine("GA engine terminated.");
        return 1;
    }
```

Please note: In `x_ArrayList, f_ArrayList, g_ArrayList, h_ArrayList`, all elements must be of type “**double**”.

6) Click **Build** -> **Build Solution**

7) Find the new DLL file here: **Project_Location\bin\Debug\Project_Name.dll**

4.3. Steps for Creating Darwin Application with C++

1) In Visual Studio, **File** -> **New** -> **Project**

2) In **Visual C++**, choose “**Win32 Console Application**”, specify **Name** e.g. “FitnessTest” (this will be the DLL file name after building later on), **Location**, and **Solution Name**, click **Next**, and then select **DLL** for application type, click **Finish**.

3) Specify the namespace (e.g. MyFitnessNameSpace), class (e.g. MyFitnessClass) and fitness function name (e.g. MyFitnessFunction). Your project source file contains as follows (Please see Appendix for a sample code).

```
#using <mscorlib.dll>
using namespace System;
using namespace System::Collections;

namespace MyFitnessNameSpace
{
    __gc public class MyFitnessClass
    {
    public:

        //constructor for one-time initialization operations, like allocating memory, etc.
        //in parallel running, each process invokes the constructor one time.
        MyFitnessClass() { }


        //destructor for one-time finialization operations, like delocating memory, etc.
        //in parallel running, each process invokes the destructor one time.
        ~MyFitnessClass() { }

        int MyFitnessFunction(ArrayList * x_ArrayList, ArrayList * f_ArrayList, ArrayList
* g_ArrayList, ArrayList * h_ArrayList, int rank, bool terminated)
        {
            if (terminated)
```

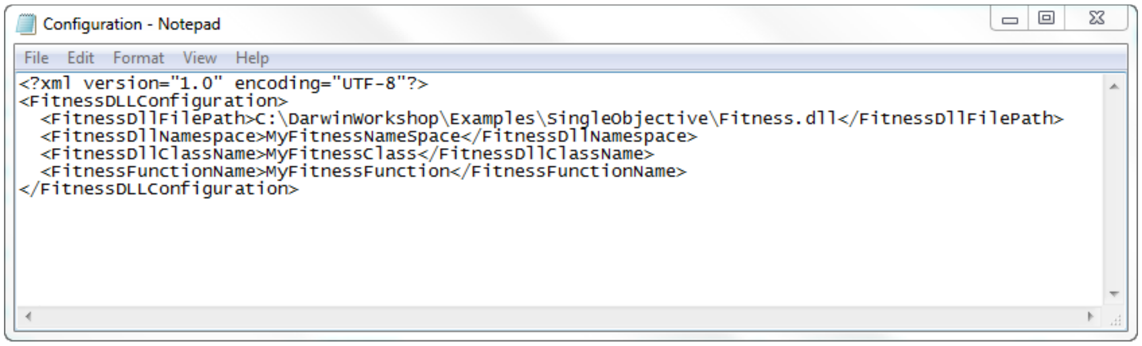
```
                {
                    Console::WriteLine("GA engine terminated.");
                    return 0;
                }

                //TODO your implementation
                return 1;
            }

        };
}
```

4) Right click the project in the **Solution Explorer**, choose **Property** to open property pages.
5) **Configuration Properties** -> **General**, in **Configuration Type** choose **Dynamic Library (.dll)** in the dropdown menu, and in **Common Language Runtime support** choose **Common Language Runtime Support, Old Syntax (/clr:oldSyntax)**.
6) Click **Build** -> **Build Solution**.
7) Find the new DLL file here: **Project_Location\Debug\Project_Name.dll**

5. RUN DARWIN OPTIMIZATION

5.1. Prepare Darwin Configuration File

Darwin configuration file is a XML file for specifying ***the path of the application fitness DLL file as well as the namespace, class name and fitness function name***. Darwin framework uses "**Configuration.xml**" (please note this file name is fixed) file to locate the fitness function DLL and exact fitness function for the run. For a new application, you can edit the sample configuration file with corresponding path, name space, class name and fitness function name, and ***save the edited file in the same folder as decision variable file***. A sample **Configuration.xml** file is shown below.



```
<?xml version="1.0" encoding="UTF-8"?>
<FitnessDLLConfiguration>
  <FitnessDllFilePath>C:\DarwinWorkshop\Examples\SingleObjective\Fitness.dll</FitnessDllFilePath>
  <FitnessDllNamespace>MyFitnessNameSpace</FitnessDllNamespace>
  <FitnessDllClassName>MyFitnessClass</FitnessDllClassName>
  <FitnessFunctionName>MyFitnessFunction</FitnessFunctionName>
</FitnessDLLConfiguration>
```

The above sample shows that the fitness function is named "MyFitnessFunction" as a method of class "MyFitnessClass", under namespace "MyFitnessNameSpace", and in the file of "C:\DarwinWorkshop\Examples\SingleObjective\Bentley.Darwin.Fitness.dll".

Before running Darwin, make sure that (1) fitness DLL file is created for the application; (2) decision file (.txt) is created for the runs and (3) configuration file is edited and saved in the same folder as decision.

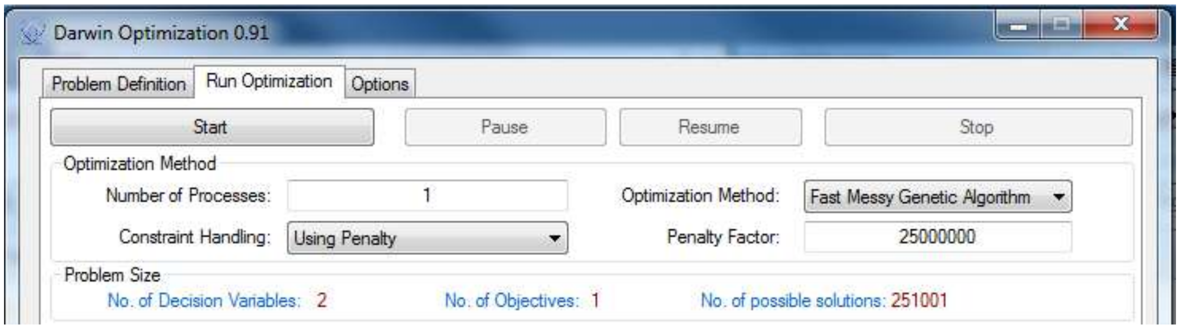
5.2. Run Darwin

Using GUI, simply click on the desktop icon . Basic steps for running Darwin are below.

Click on **Problem Definition** tab, and

1) Load decision variable file;
2) Load configuration file;
3) Change the output folder as desired.

Click on **Run Optimization** tab

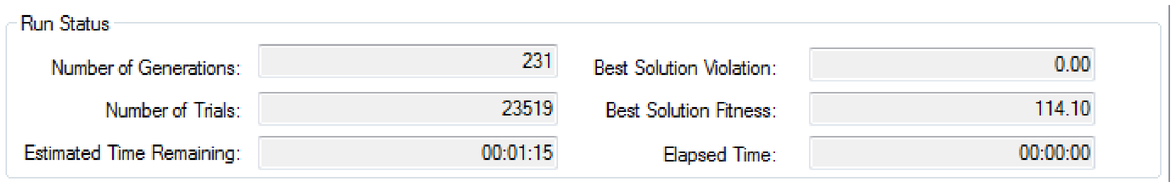


Number of Processes: 1
Optimization Method: Fast Messy Genetic Algorithm
Constraint Handling: Using Penalty
Penalty Factor: 25000000
No. of Decision Variables: 2
No. of Objectives: 1
No. of possible solutions: 251001

After decision variable file and configuration files are loaded, the problem information, including No. of Decision Variables, No. of Objectives and No. of Possible solutions, is calculated and displayed within the section of Problem Size.

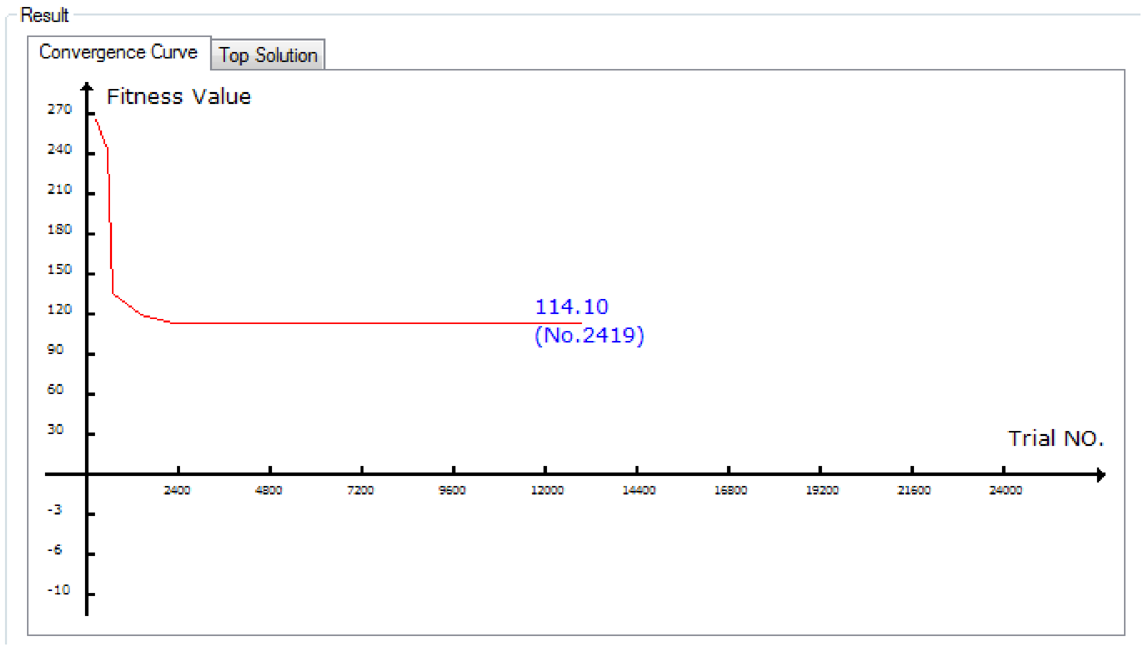
You can run Darwin in sequential optimization when Number of Process is 1 or in parallel optimization when Number of Process is greater than 1. Choose the desired optimization method and constraint handling technique, click on **Start** button to run Darwin. To pause the run, click on **Pause** button, to resume the run, click on **Resume** button. To terminate the run, click on **Stop** button.

Darwin run time status is updated during the run as below.



Number of Generations:	231	Best Solution Violation:	0.00
Number of Trials:	23519	Best Solution Fitness:	114.10
Estimated Time Remaining:	00:01:15	Elapsed Time:	00:00:00

The results of **Convergence Curve** and **Top Solutions** are also dynamically updated as follows.

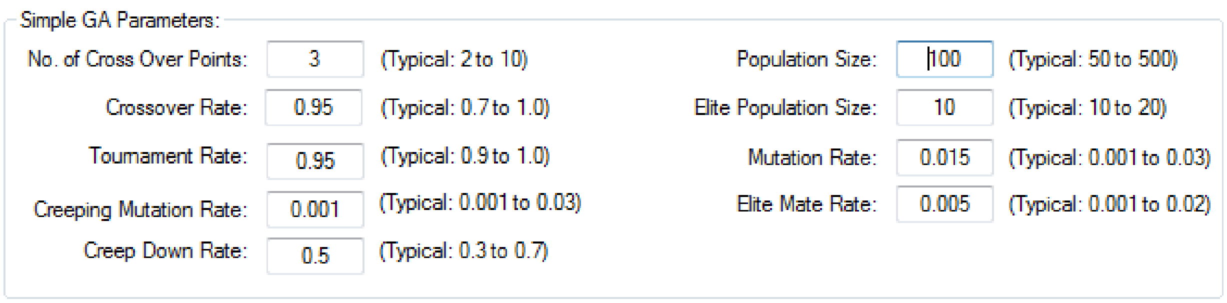


5.3 Darwin Options

Under **Options** tab, three sections of data including GA Parameters, Stopping Criteria and Options, are specified as below.

GA Parameters

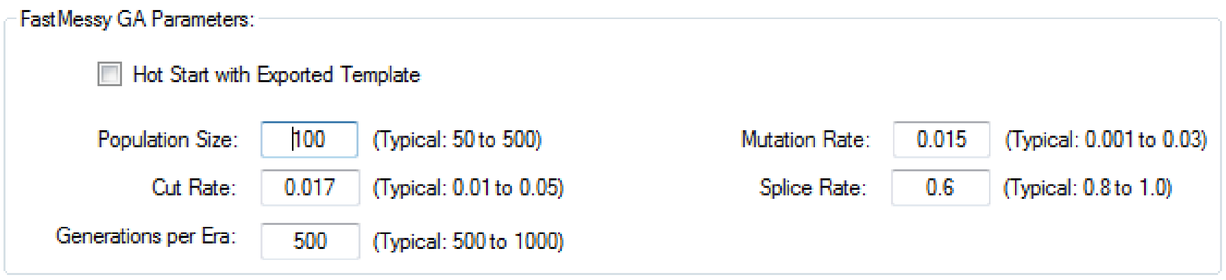
If simple GA is selected for the run, the following GA parameters are used below.



Simple GA Parameters:

No. of Cross Over Points:	3	(Typical: 2 to 10)	Population Size:	100	(Typical: 50 to 500)
Crossover Rate:	0.95	(Typical: 0.7 to 1.0)	Elite Population Size:	10	(Typical: 10 to 20)
Tournament Rate:	0.95	(Typical: 0.9 to 1.0)	Mutation Rate:	0.015	(Typical: 0.001 to 0.03)
Creeping Mutation Rate:	0.001	(Typical: 0.001 to 0.03)	Elite Mate Rate:	0.005	(Typical: 0.001 to 0.02)
Creep Down Rate:	0.5	(Typical: 0.3 to 0.7)			

If the fmGA is selected for the run, the GA parameters are as follows.



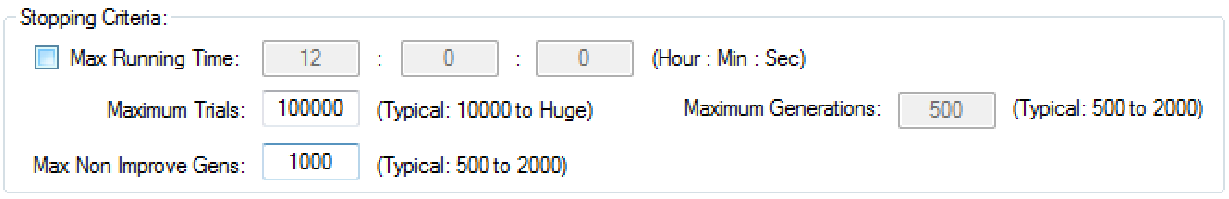
FastMessy GA Parameters:

☐ Hot Start with Exported Template

Population Size:	100	(Typical: 50 to 500)	Mutation Rate:	0.015	(Typical: 0.001 to 0.03)
Cut Rate:	0.017	(Typical: 0.01 to 0.05)	Splice Rate:	0.6	(Typical: 0.8 to 1.0)
Generations per Era:	500	(Typical: 500 to 1000)			

Hot Start with Exported Template: if checked, the best chromosome exported from previous run using fmGA will be used as template for the current run. The template serves as hot start and speed up the convergence to the near optimal solutions.

Stopping Criteria



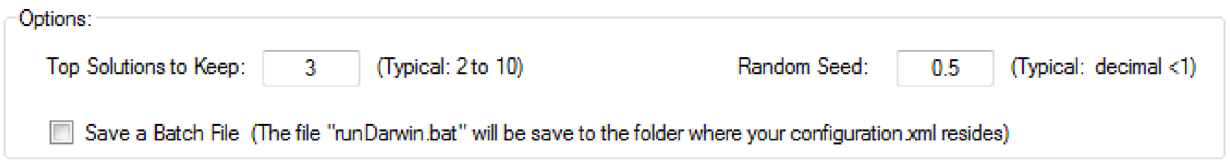
Stopping Criteria:

☐ Max Running Time: 12 : 0 : 0 (Hour : Min : Sec)

Maximum Trials:	100000	(Typical: 10000 to Huge)	Maximum Generations:	500	(Typical: 500 to 2000)
Max Non Improve Gens:	1000	(Typical: 500 to 2000)			

1) Maximum Running Time: Darwin run will be terminated after the specified time is used up.
2) Maximum Trials: Darwin run will be terminated after reaching the maximum number of trial solutions.
3) Max Non Improve Gens: Darwin run will be terminated if the best solution is not improved after the maximum number of non-improvement generations.
4) Maximum Generations: If simple GA is used, Darwin will be terminated if the number of generation reaches the maximum generations.

Options



Options:

Top Solutions to Keep:	3	(Typical: 2 to 10)	Random Seed:	0.5	(Typical: decimal <1)

☐ Save a Batch File (The file "runDarwin.bat" will be save to the folder where your configuration.xml resides)

1) Top Solution to Keep: specify the number of near-optimal solutions to save for the single objective optimization. For Multi-objective solution, all Pareto solutions are saved for the run.
2) Random Seed: specify the seed for generating initial population of solution.
3) Save a Batch File: if checked, a batch file will be created to run Darwin in console prompt. Simply click the batch file to run Darwin in Console. A sample batch file for parallel optimization run is created and listed below.

```
@echo off
mpiexec.exe -n 3 C:\PROGRA~2\Bentley\DARWIN~1\Bin\Bentley.Darwin.Console.exe FastMessyGA
C:\DARWIN~1\Examples\SINGLE~1\DECISI~1.TXT C:\Users\zheng.wu\AppData\Local\DARWIN~2\GA_parameters.txt violation
C:\Users\zheng.wu\AppData\Local\DARWIN~2\TopSolution.txt
pause
```

5.4 Start Darwin Using Command

Apart from running Darwin in console using batch file created by GUI, in general, Darwin can be run with the following command and arguments.

1) Start Darwin GUI using command line:

   Open console prompt and change directory to the folder where decision variable file and configuration file are located, use the following command to start Darwin GUI:

   [Darwin bin path]\Bentley.Darwin.GUI2.exe decision_file.txt

   ```
   C:\PROGRA~2\Bentley\DARWIN~1\Bin\Bentley.Darwin.GUI2.exe C:\DARWIN~1\Examples\SINGLE~1\DECISI~1.TXT
   ```

2) Sequential optimization run command (use the same folder with .exe to eliminate [path+]):

   Bentley.Darwin.Console.exe type_of_GA [path+]decision_file.txt [path+]parameter_file.txt [type_of_constrant_handling_method] [path+]log_file.txt

3) Parallel optimization command (use the same folder with .exe to eliminate [path+]):

   Mpiexec –n 4 Bentley.Darwin.Console.exe type_of_GA [path+]decision_file.txt [path+]parameter_file.txt [type_of_constrant_handling_method] [path+]TopSolution_file.txt

   a. MPI should be installed and is need to start the parallel application.

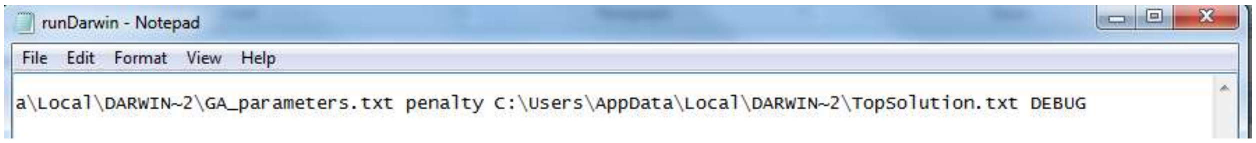
   b. type_of_GA: “FastMessyGA” for fast messy Genetic Algorithm; “SimpleGA” for simple Genetic Algorithm.

c. Constraint handling methods. For “FastMessyGA”, two methods are available for handling constraints, “penalty” or “violation”. For “SimpleGA”, this argument is eliminated, which uses “penalty” to handle constraints.

d. TopSolution_file.txt: result file that contains the top solutions found by Darwin optimization engine.

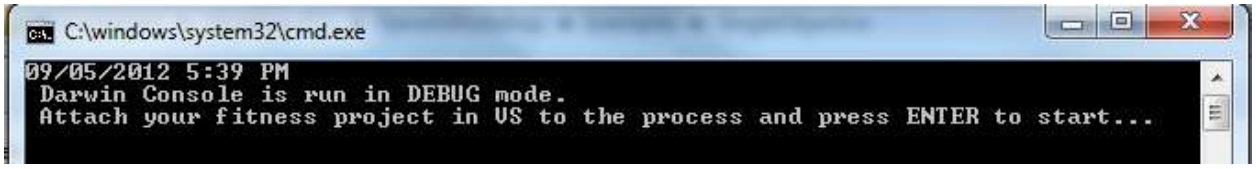
5.5 Debug Darwin Applications

It is important to be able to debug the fitness implementation. In order to do so, Darwin needs to be launched in console. Simply add DEBUG to the end of command line or in the batch file, such as:



```
a\Local\DARWIN~2\GA_parameters.txt penalty C:\Users\AppData\Local\DARWIN~2\TopSolution.txt DEBUG
```

When running Darwin in console with DEBUG argument, the run process will pause as below.



```
09/05/2012 5:39 PM
 Darwin Console is run in DEBUG mode.
 Attach your fitness project in VS to the process and press ENTER to start...
```

Darwin run process can be then attached with the fitness project for debugging.

6. EXAMPLES

6.1. Single Objective Optimization Fitness Code (C#)

```
using System;
using System.Collections;

namespace MyFitnessNameSpace
{
    public class MyFitnessClass
    {
        //constructor for one-time initialization operations, like allocating memory, etc.
        //in parallel running, each process invokes the constructor one time.
        MyFitnessClass() { }


        //destructor for one-time finialization operations, like delocating memory, etc.
        //in parallel running, each process invokes the destructor one time.
        ~MyFitnessClass() { }

         #region Fitness Calculation method

         public int MyFitnessFunction(ArrayList x_ArrayList, ArrayList f_ArrayList,
ArrayList g_ArrayList, ArrayList h_ArrayList, int rank, bool terminated)
```

```
        {
            if (terminated)
            {
                Console.WriteLine("GA engine terminated.");
                return 0;
            }
            //Console.WriteLine("x_ArrayList come form rank = " + rank);

            //TODO: Implement the function- User defined
            f_ArrayList.Clear();
            g_ArrayList.Clear();
            h_ArrayList.Clear();

            /* objective function */
            f_ArrayList.Add(10.0 * (double)x_ArrayList[0] + 11.0 *
(double)x_ArrayList[1]);

            double g_value;
            /* constraints g<=0 */

            g_value = 11 - ((double)x_ArrayList[0] + (double)x_ArrayList[1]);
            if (g_value <= 0) g_value = 0;
            g_ArrayList.Add(g_value);

            g_value = (double)x_ArrayList[0] - (double)x_ArrayList[1] - 5;
            if (g_value <= 0) g_value = 0;
            g_ArrayList.Add(g_value);

            g_value = 35 - (7.0 * (double)x_ArrayList[0] + 12.0 *
(double)x_ArrayList[1]);
            if (g_value <= 0) g_value = 0;
            g_ArrayList.Add(g_value);


            return 1;
        }
        #endregion
    }
}
```

6.2. Single Objective Optimization Fitness Code (C++)

```
#using <mscorlib.dll>
using namespace System;
using namespace System::Collections;

namespace MyFitnessNameSpace
{
    __gc public class MyFitnessClass
    {
    public:
        //constructor for one-time initialization operations, like allocating memory, etc.
        //in parallel running, each process invokes the constructor one time.
        MyFitnessClass() { }


        //destructor for one-time finialization operations, like delocating memory, etc.
        //in parallel running, each process invokes the destructor one time.
        ~MyFitnessClass() { }

        int MyFitnessFunction(ArrayList * x_ArrayList, ArrayList * f_ArrayList, ArrayList
* g_ArrayList, ArrayList * h_ArrayList, int rank, bool terminated)
        {
            if (terminated)
            {
                Console::WriteLine("GA engine terminated.");
                return 0;
            }
            //Console.WriteLine("x_ArrayList come form rank = " + rank);

            //TODO: Implement the function- User defined
            f_ArrayList->Clear();
            g_ArrayList->Clear();
            h_ArrayList->Clear();

            /* objective function */
           IEnumerator * temp = x_ArrayList->GetEnumerator(0,2);
           temp ->MoveNext();
           double tempx0 = *dynamic_cast<__box Double*>(temp->Current);
           temp ->MoveNext();
           double tempx1 = *dynamic_cast<__box Double*>(temp->Current);
           f_ArrayList->Add(__box(10.0 * tempx0 + 11.0 * tempx1));

            double g_value;
            /* constraints g<=0 */

            g_value = 11 - (tempx0 + tempx1);
            if (g_value <= 0) g_value = 0;
            g_ArrayList->Add(__box(g_value));

            g_value = tempx0 - tempx1 - 5;
            if (g_value <= 0) g_value = 0;
            g_ArrayList->Add(__box(g_value));

            g_value = 35 - (7.0 * tempx0 + 12.0 * tempx1);
            if (g_value <= 0) g_value = 0;
            g_ArrayList->Add(__box(g_value));


            return 1;
        }

    };
}
```

6.3. Multiple Objective Optimization (using fast messy GA)

This example problem is formulated as follows.

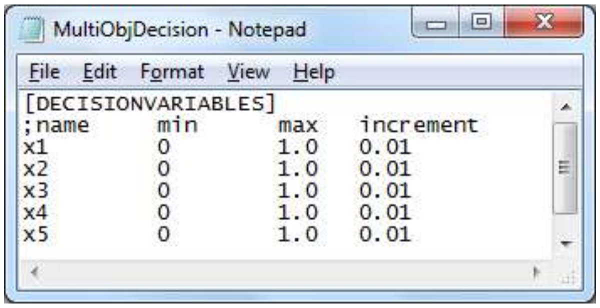
Minimize: $O_1: 1 - e^{-4x_1}(\sin 6\pi x_1)^6$

O_2: g * h

Subject to: $C_1: 0 \ll x_i \ll 1\ i \in \{1,2,3,4,5\}$

Where: $g = 1 + 9[(\sum_{i=2}^{10} x_i)/9]^{0.25}$, and $h = 1 - (\frac{O_1}{g})^2$.

1) Create decision file (MultiOjbDecision.txt) of variables to be determined and capture constraint C_4 as follows:



```
[DECISIONVARIABLES]
;name       min         max    increment
x1          0           1.0    0.01
x2          0           1.0    0.01
x3          0           1.0    0.01
x4          0           1.0    0.01
x5          0           1.0    0.01
```

2) Create new DLL file of the fitness as stated in the section of Implement Darwin Fitness Application. C# sample codes are in the next section.

3) Create "Configuration.xml" file as follows (it is recommended to move the decision file, parameter file, and DLL file to a folder of convenience before this step). Replace [PathToDLLFile\] accordingly.

```
<?xml version="1.0" encoding="UTF-8" ?>
  <FitnessDLLConfiguration>
  <FitnessDllFilePath>[PathToDLLFile\]MultiObjFitness.dll</FitnessDllFilePath>
  <FitnessDllNamespace>MyFitnessNameSpace</FitnessDllNamespace>
  <FitnessDllClassName>MyFitnessClass</FitnessDllClassName>
  <FitnessFunctionName>MultiObjective</FitnessFunctionName>
  </FitnessDLLConfiguration>
```

4) Place "Configuration.xml" under the same folder as the decision variable file.

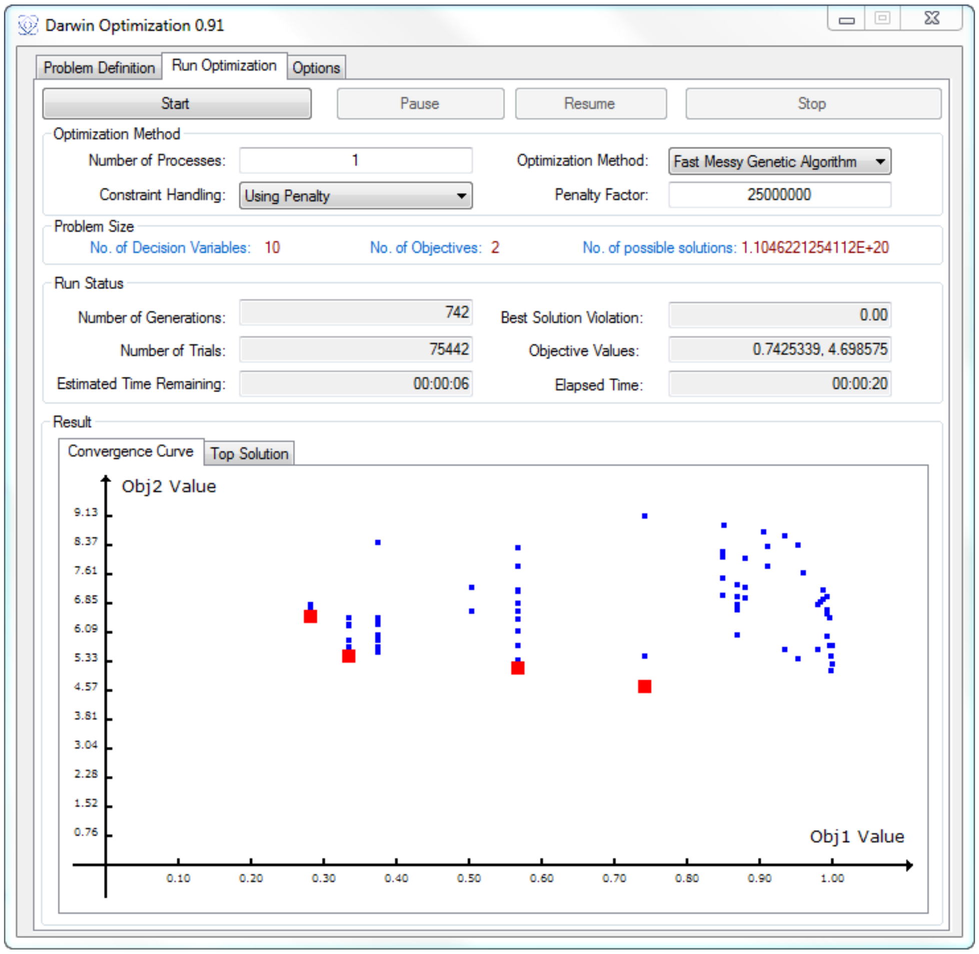
5) Start Darwin, load the corresponding decision file and configuration file, and make sure to select **Fast Messy Genetic Algorithm** for the run.

6) Top (Pareto) solutions will be plotted at run time and also saved in the TopSolutions.txt.

The C# code for this example is listed below.

```
using System;
using System.Collections;
using System.Linq;
using System.Text;

namespace MyFitnessNameSpace
{
    public class MyFitnessClass
    {
        #region Fitness Calculation method
        public int MultiObjective(ArrayList x_ArrayList, ArrayList f_ArrayList, ArrayList
g_ArrayList, ArrayList h_ArrayList, int rank, bool terminated)
        {
            if (terminated) return 1;

            f_ArrayList.Clear();
            g_ArrayList.Clear();
            h_ArrayList.Clear();

            double x1 = (double)x_ArrayList[0];
            double f1 = 1 - Math.Exp((double)(-4) * x1) * Math.Pow(Math.Sin(x1 * 6 * 3.1415926),
6);
            double g = 0.0F;
            for (int nIndex = 1; nIndex < x_ArrayList.Count; nIndex++)
                g += (double)x_ArrayList[nIndex];
            g = 1 + 9 * Math.Pow((double)g / (double)9, 0.25);
            double h = 1 - Math.Pow((f1 / g), 2);
            double f2 = g * h;
            f_ArrayList.Add(f1);
            f_ArrayList.Add(f2);
            return 1;
        }
        #endregion
    }
}
```

Sample run of the multi objective optimization example is shown as below.



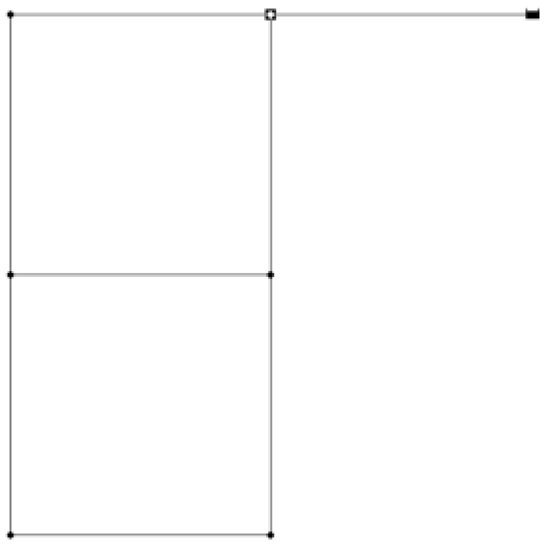
Number of Processes: 1
Optimization Method: Fast Messy Genetic Algorithm
Constraint Handling: Using Penalty
Penalty Factor: 25000000

No. of Decision Variables: 10
No. of Objectives: 2
No. of possible solutions: 1.1046221254112E+20

Number of Generations: 742
Best Solution Violation: 0.00
Number of Trials: 75442
Objective Values: 0.7425339, 4.698575
Estimated Time Remaining: 00:00:06
Elapsed Time: 00:00:20

6.4. Engineering Application Example: Water Distribution System Optimization

This example demonstrates then application of Darwin to solving an engineering optimization problem. It is specified to optimize pipe sizes (diameters) so that the total cost of design is minimized and the pressures at nodes meet the minimum pressure requirement. The example system used is Twoloop network the benchmark example used in the literature. The system layout is shown below.

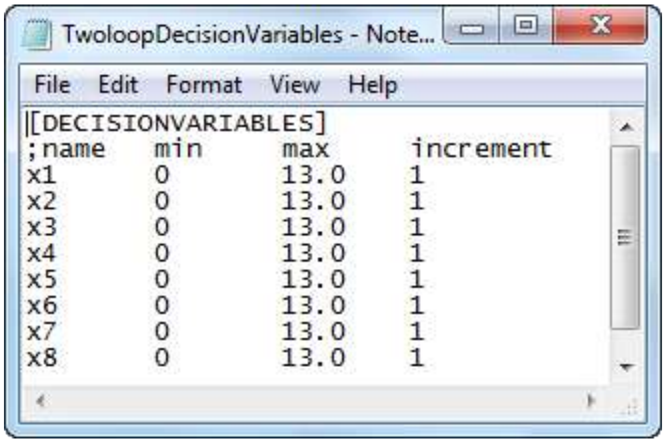


Layout of Twoloop Network

The system contains 8 pipes to be sized or optimized, each of the 8 pipes with length of 1000 meters can take a size from the available possible diameters (14 of them) as specified below.

```
diam[]     = {25.4,50.8,76.2,101.6,152.4,203.2,254.0,304.8,355.6,406.4,457.2,508.0,558.8,609.0};
unitcost[] = {2.0, 5.0, 8.0,11.0, 16.0, 23.0, 32.0, 50.0, 60.0, 90.0, 130.0,170.0, 300.0,550.0};
```

The objective is to minimize the total cost of pipes. The cost for each pipe is calculated by multiplying the pipe length (1000) with the unit-length cost ($/meter) for the corresponding pipe size. The unit-length cost is given in unitcost[ ] as above. Each pipe is allowed to take any of 14 possible diameter sizes from `diam[]`. To optimize the pipe sizes, the diameter index is used as decision variable, which can take a value from 0 to 13, for instance, 0 diameter index from `diam[]` for a pipe is representing diameter of 25.4 mm. Therefore, the decision variable file is defined for 8 pipes as follows.


TwoloopDecisionVariables - Note...
File Edit Format View Help

```
[DECISIONVARIABLES]
;name   min     max     increment
x1      0       13.0    1
x2      0       13.0    1
x3      0       13.0    1
x4      0       13.0    1
x5      0       13.0    1
x6      0       13.0    1
x7      0       13.0    1
x8      0       13.0    1
```

The constraint for this example is to satisfy the minimum pressure head of 30.0 meters at the junctions (6 of them). EPANET2 toolkit is used for the implementation. The toolkit contains a set of APIs for executing analysis runs, updating and retrieving model attributes.

As installed with Darwin, this example is implemented in WDSOptimizaiton solution, which contains two projects, including WDSFitness and WDSEvaluation.

WDSFitness project is implemented as follows.

```
#using <mscorlib.dll>

#include "interface.h"
using namespace System;
using namespace System::Collections;
using namespace System::Runtime::InteropServices;

namespace MyFitnessNameSpace
{
    __gc public class MyFitnessClass
    {
    public:

       MyFitnessClass()
       {
              OpenEngine();
       }

       ~MyFitnessClass()
       {
       //close epanet engine
              CloseEngine();
       }

       int TwoLoopFitnessFunction(ArrayList * x_ArrayList, ArrayList * f_ArrayList, ArrayList *
       g_ArrayList, ArrayList * h_ArrayList, int rank, bool terminated)
      {

       if (terminated)
        {
       Console::WriteLine("Darwin is terminated.");
        return 0;
        }
       // clear array lists
```

```
        f_ArrayList->Clear();
        g_ArrayList->Clear();
        h_ArrayList->Clear();

        //preparing new solution for evaluation
        int nx = x_ArrayList->Count;
        Int32 index[] = new Int32[nx];
        for(int i=0;i<nx;++i)
                index[i] = *dynamic_cast<__box double*>(x_ArrayList->get_Item(i));

        int __pin* xList = &index[0];
        double violation = 0.0;
        double totalcost = 0.0;
        objFunction(xList,nx,&violation,&totalcost);

        f_ArrayList->Add(__box(totalcost));
        g_ArrayList->Add(__box(violation));

        return 1;
        }
    }
}
```

WDSFitness is set up as a managed C++ project. It opens EPANET analysis engine in the constructor and close the engine in the destructor. The fitness function `TwoLoopFitnessFunction(ArrayList * x_ArrayList, ArrayList * f_ArrayList, ArrayList * g_ArrayList, ArrayList * h_ArrayList, int rank, bool terminated)` is implemented to receive the new solution from Darwin and evaluate it in the function **`objFunction`**`(xList,nx,&violation,&totalcost)` , which is implemented along with `OpenEngine()` and `CloseEngine()` in the C/C++ project of WDSEvaluation.

WDSEvaluation.cpp code is below.

```
#define LPLIBRARY_EXPORT
#include "interface.h"
#include "epanet2.h"

        float diam[] =
{25.4,50.8,76.2,101.6,152.4,203.2,254.0,304.8,355.6,406.4,457.2,508.0,558.8,609.0};
        float unitcost[] = {2.0, 5.0, 8.0,11.0, 16.0, 23.0, 32.0, 50.0, 60.0, 90.0, 130.0,170.0,
300.0,550.0};
        static float pipelength = 1000.0;
        static float minpressure = 30.0;

        double LPAPI objFunction(int *xList, int xListSize, double *violation, double *objvalue)
        {
                //calculate cost objective function;
                *objvalue = 0.0;
                for (int i = 0; i < xListSize; i++){
                        *objvalue +=pipelength*unitcost[xList[i]];
                        int linkindex = i+1;
                        //set new diameters (new solution) to the analysis engine
                        ENsetlinkvalue(linkindex, EN_DIAMETER,diam[xList[i]]);
                };
                //run epanet analysis engine
                ENsetstatusreport(0);
                ENsetreport("MESSAGES NO");
                ENinitH(0);
                ENsolveH();
                //check constraint(nodal pressure) violation
                float pressure;
                *violation = 0.0;
```

```
		for (int i = 1; i <= 6; i++){ //6 junctions in twoloop model
			ENgetnodevalue(i, EN_PRESSURE, &pressure);
			if (pressure < minpressure){
				*violation += minpressure - pressure;
			};
		};

		return(1.0);
	}

	int LPAPI OpenEngine()
	{
		// open model files
		int errNum = ENopen("twoloop.inp", "twoloop.rpt", "");
		//printf("ENopen errNum = %d \n", errNum);
		if (errNum != 0){
			printf("ENopen errNum = %d \n", errNum);
			ENclose();
		};
		//open epanet analysis solver
		ENopenH();
		//printf("\n openH err = %i", errNum);
		if (errNum != 0){
			ENcloseH();
			ENclose();
			printf("ENopen errNum = %d \n", errNum);
		};

		return(1);
	}

	int LPAPI CloseEngine()
	{
		//close epanet analysis engine
		ENcloseH();
		ENclose();

		return(1);
	}
```

objFunction( ) receives new solution (new diameter index for each pipe) in xList, calculates the total pipe cost (as assigned to *objvalue), sets the new diameters to EPANET engine, runs the hydraulic simulation with the new diameters, retrieves nodal pressure and checks for pressure constraint violation.

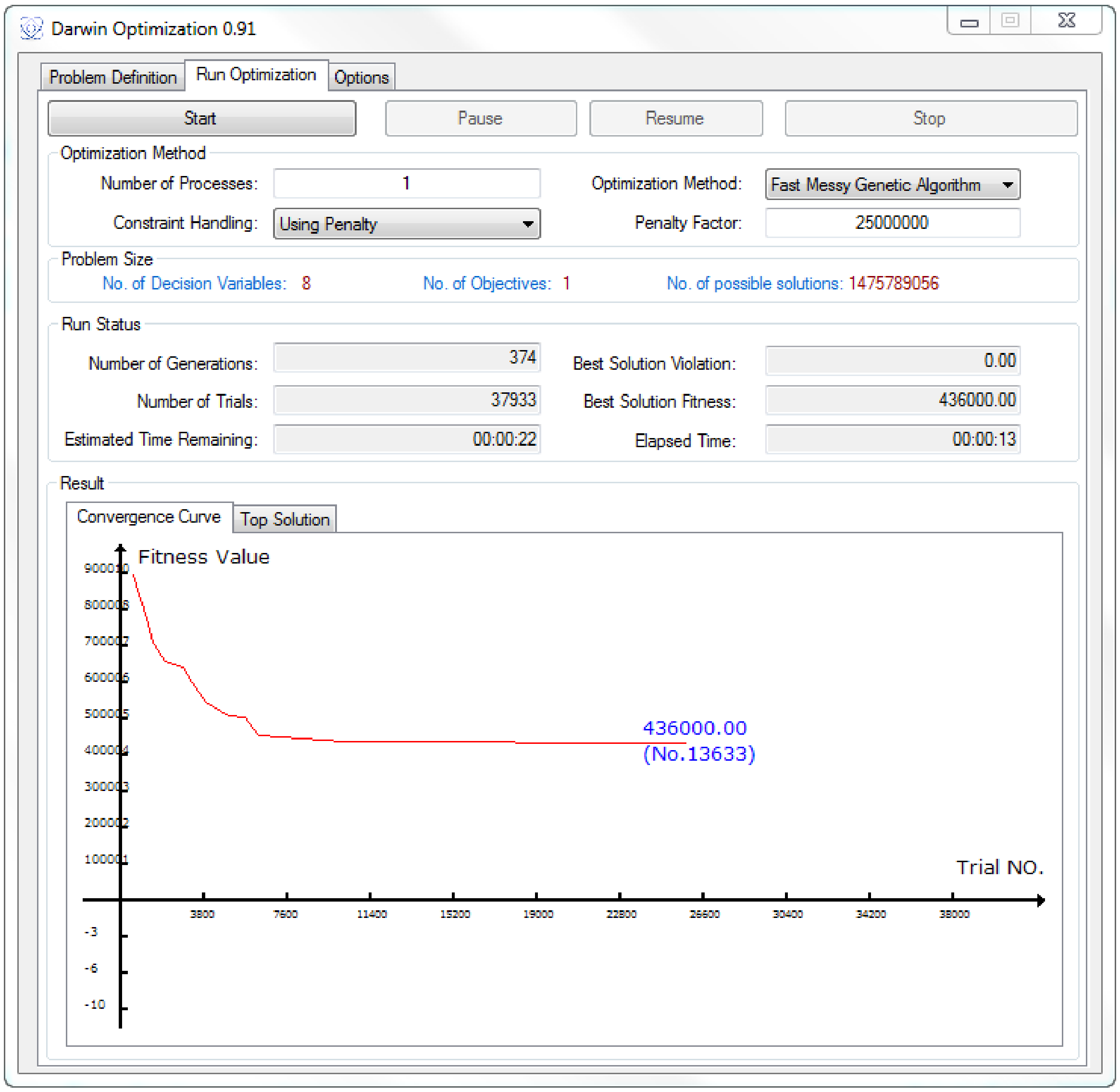
Within WDSEvaluation project, three functions, including objFunction( ), OpenEngine( ) and CloseEngine( ) are implemednted and published or exported for being used in WDSFitness project. The prototype of the published APIs is specified in interface.h.

Interface.h code is below.

```
#pragma once

#if defined(LPLIBRARY_EXPORT) // inside DLL
#   define LPAPI    __declspec(dllexport)
#else // outside DLL
#   define LPAPI    __declspec(dllimport)
#endif  // LPLIBRARY_EXPORT

#include <stdio.h>

extern "C"{
               double LPAPI objFunction(int *,int, double *, double *);
               int LPAPI OpenEngine();
               int LPAPI CloseEngine();
        }
```

To run this example, follow the steps below:

1) Open MS VS (2008 or newer version), and load the solution WDSOptimization from folder C:\DarwinWorkshop\Examples\WDSOptimization (or the folder where the Examples are copied to).
2) Click on Build->Build Solution, the solution will be built with two DLLs created in folder ..\Examples\WDSOptimization\Release, or debug folder if build in debug mode.
3) Copy WDSEvalution.dll and WDSFitness.dll into C:\DarwinWorkshop \Examples\WDSObjective
4) Click Darwin icon on desktop to start Darwin.
5) Load decision variable file TwoloopDecisionVariables.txt from C:\DarwinWorkshop\Examples\WDSObjective, the configuration file in the same folder will be automatically loaded, make sure the path and fitness dll file name are correct.
6) Change the output folder as desired, then you can run the application as shown below.



Darwin Optimization 0.91

Problem Definition | Run Optimization | Options

Start | Pause | Resume | Stop

Optimization Method

Number of Processes: 1

Optimization Method: Fast Messy Genetic Algorithm

Constraint Handling: Using Penalty

Penalty Factor: 25000000

Problem Size

No. of Decision Variables: 8 No. of Objectives: 1 No. of possible solutions: 1475789056

Run Status

Number of Generations: 374

Best Solution Violation: 0.00

Number of Trials: 37933

Best Solution Fitness: 436000.00

Estimated Time Remaining: 00:00:22

Elapsed Time: 00:00:13

Result

Convergence Curve | Top Solution

TECHNIQUE REFERENCE: DARWIN OPTIMIZATION METHOD

The framework encapsulates the core methodology for solving single and multiple objective optimization problems, the techniques for handling equality and inequality constraints, and also provides the options for executing solution evaluation/fitness in multiple processes as needed. It decouples the parallel optimization solver from domain applications and enables rapid implementation of infrastructure optimization projects with thin-client architecture. The parallel optimization is based on the competent genetic algorithm that has successfully applied to water distribution optimization problems including model calibration, network design and pump scheduling. The framework has recently been applied to geometry design optimization, building energy performance-based design optimization, finite element analysis model updating (calibration) and damage detection for civil infrastructure health monitoring (Wu, Wang, Butala, & Mi, 2011) [1]. The generalized Darwin framework contains both simple GA and fast messy GA as optimization solvers.

6.5. Simple Genetic Algorithm

A genetic algorithm is a search method that emulates the principles of genetic reproduction operations such as crossover and mutation. It is a branch of evolutionary computation and formally introduced by Holland in 1975 (Holland 1975) [2]. Since then, genetic algorithm has been one of the most active research fields in artificial intelligence. Many successful applications have been made in engineering, science, economy, finance, business and management. There are many variations of GA, but basic idea is as follows.

GA represents a solution as a string, for instance a binary string as shown in Figure 7.1. It can be any other type of strings. The string is referred to as phenotype or chromosome. One segment of string is assigned to represent one decision variable (e.g. one leak) and thus one completed solution (e.g. a number of leaks for a water distribution system) is encoded onto one string as shown in Figure 7.1.

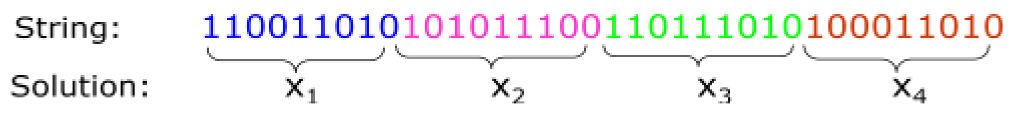


Figure 7.1 An example of genetic algorithm solution representation

Initially, a population of strings or solutions is randomly created. Each of the solutions is evaluated by performing the corresponding hydraulic simulation (either steady state or transient analysis). A fitness value can be calculated by the objective function and assigned to the solution or string. By emulating the principle of Darwin's *survival-of-fittest*, the better solution is selected as parent to reproduce next generation of solution. Figure 7.2 illustrates operation of selecting two parents.

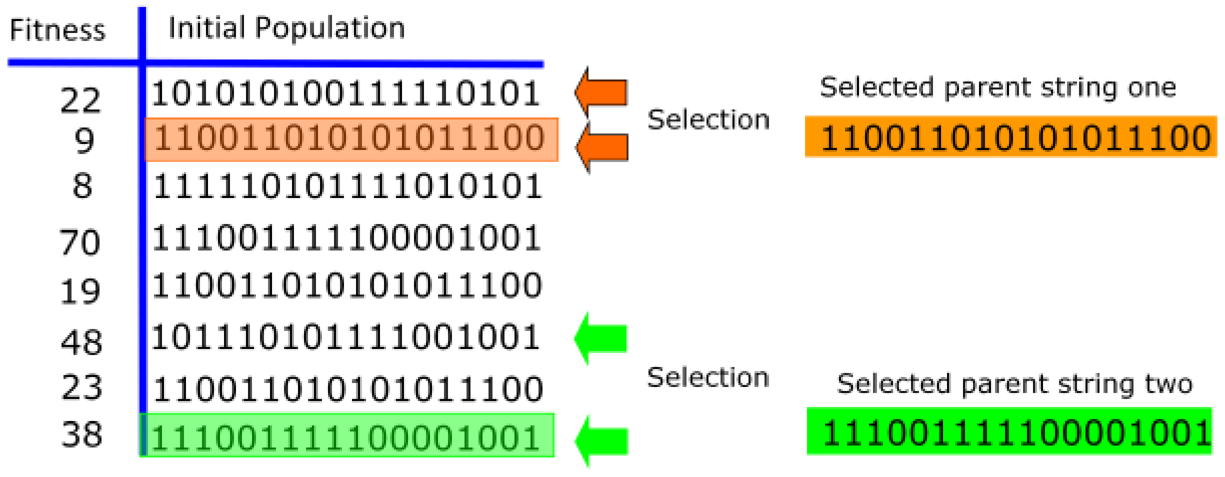


Figure 7.2 Example GA population solutions and selection operation

The selected parent strings are to reproduce offspring namely the child solutions. Two operations of crossover and mutation are mimicked for the reproduction. As shown in Figure 7.3, crossover is to first cut two strings at a randomly selected crossover point and then exchanges partial chromosomes to form two new child solutions.

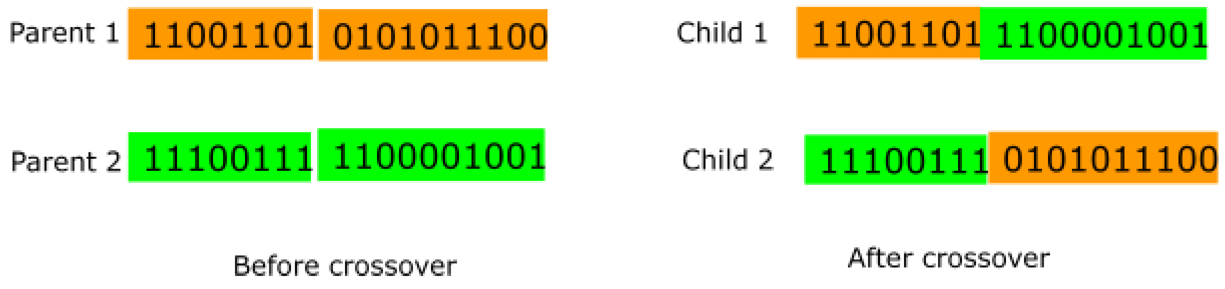

Parent 1 11001101 0101011100
Parent 2 11100111 1100001001
Before crossover
Child 1 11001101 1100001001
Child 2 11100111 0101011100
After crossover

Figure 7.3 Genetic algorithm crossover operations

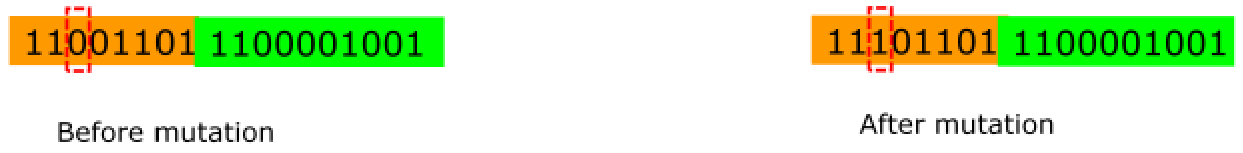


Figure 7.4 Genetic algorithm mutation operations

After crossover, a new solution may be mutated by changing the bit value. As illustrated in Figure 7.4, a bit may be selected as highlights and its value is flipped from 0 to 1 (or1 to 0). Both crossover and mutation are applied by performing a probabilistic test and when its probability is greater than the prescribed probability. Repetitively applying selection, crossover and mutation, a new population of solutions can be reproduced, and each of them is evaluated with a fitness value. This far, one generation is completed. Generation after generation, the population of strings are expected to evolve to optimal or near-optimal solution.

This is the basic procedure of simple GA. There are different variations based on the principles of the simple genetic algorithm. The improvement of the existing GA methods and new GAs have been constantly developed and reported in literature every year. Overall, many advantages are identified for GA search for good solutions (Goldberg 1989). The primary merit is its capability of solving nonlinear optimization problems. Model-based leakage detection is a typical implicit nonlinear optimization problem.

6.6. Fast Messy Genetic Algorithm Key Features

Similar to simple GA, but fast messy GA (fmGA) is different with the key features including flexible string length, gene filtering and multi-era search process. It is originally developed as one of the competent genetic algorithms (Goldberg 2001) [3] for solving the hard-problems more efficiently and effectively.

With fmGA, a flexible scheme is employed to represent a calibration solution with strings (chromosomes) of variable lengths. The length of strings changes from one string to another. Short strings namely partial solutions are generated and evaluated during the early stage of GA optimization. The short strings with better fitness value above the average are considered to retain “building blocks” that form the good solutions. The fmGA starts with an initial population of full-length strings and follows by a building block filtering process. It identifies the better fit short strings by randomly deleting genes from the initial strings. The identified short strings are used to generate new solutions. A solution is formed by “cut” and “splice” operations instead of standard GA crossover. “Cut” divides one string into two strings while “splice” link two strings to create one individual string. Both genetic operations are purposely designed to effectively exchange the building blocks for generating good solutions.

The fmGA combines building block identification and solution reproduction phases into one artificial evolution process and proceeds over a number of outer iterations or so-called eras. Each era consists of solution initialization, building block filtering and reproduction. The eras continue until good solutions are found or computation resources reach the maximum limit. The fmGA is employed as a competent optimizer for evolving effective water distribution models and embedded into a multi-tier modeling software System (Bentley 2006 [4] and Haestad 2002 [5]).

6.7. Parallelism Paradigms

The software world has been very active part of the evolution of parallel computing. As multi-core processors bring parallel computing to mainstream customers, the key challenge in computing today is to transition the software industry to parallel programming. Parallel programs have been harder to write than sequential ones. A program that is divided into multiple concurrent tasks is more difficult to implement, due to the necessary synchronization and communication that needs to take place between those tasks. Some standards have emerged. There are two types of computation parallelism at instruction level, data parallelism and task parallelism. Both data and task parallelisms can be achieved by different programming languages, libraries and application programming interfaces (APIs). Message passing interface (MPI) [6] and Open Multi-Processor (OpenMP) [7] are among the most commonly-used libraries for task parallelism and data parallelism.

6.7.1. Task parallelism

Task parallelism is a parallel computing program that a computing problem is divided into many computing tasks and that different calculations can be performed on different computing processes (CPUs or nodes). Each of the computing tasks can be performed with either the same or different sets of data. Task parallelism usually scales with the number of computing nodes. There are various methods for achieving task parallelism computing, a message passing communication is usually employed for a scalable and portable implementation.

Message Passing Interface is a specification of the application programming interface (API) that allows many computers to communicate with one another. It is used for parallelizing computing task over a cluster of machines or on supercomputers, where each of the CPU is representing a computing node or process. It is a language-independent communications protocol supporting both point-to-point and collective communication. MPI is designed for developing high performance computing applications with scalability and portability. It is one of the popular models used in high-performance computing.

MPI consists of more than 115 functions [8]. Various MPI implementations are as follows.

1) DeinoMPI [9] is an implementation of MPI-2 for Microsoft Windows. This is the release version 1.1.0 with downloads for both Win32 and Win64 machines.
2) PureMPI.NET [10] is a completely managed implementation of the message passing interface. The object-oriented API is simple, and easy to use for parallel programming. It has been developed based on the latest .NET technologies, including Windows Communication Foundation (WCF). This allows you to declaratively specify the binding and endpoint configuration for your environment, and performance needs. When using the SDK, a programmer will definitely see the MPI'ness of the interfaces come through, and will enjoy taking full advantage of .NET features - including generics, delegates, asynchronous results, exception handling, and extensibility points.
3) MPI.NET [11] is a high-performance, easy-to-use implementation of the Message Passing Interface (MPI) for Microsoft's .NET environment. MPI is the *de facto* standard for writing parallel programs running on a distributed memory system, such as a compute cluster, and is widely implemented. Most MPI implementations provide support for writing MPI programs in C, C++, and FORTRAN. MPI.NET provides support for all of the .NET languages (especially C#), and includes significant extensions (such as automatic serialization of objects) that make it far easier to build parallel programs that run on clusters.
4) MPICH2 is a high-performance and widely portable implementation of the Message Passing Interface (MPI) standard (both MPI-1 and MPI-2). The goals of MPICH2 is to provide an MPI

implementation that efficiently supports different computation and communication platforms including commodity clusters, high-speed networks and proprietary high-end computing systems.

5) MSMPI [12] is the Microsoft's implementation of MPICH2 for Windows Compute Cluster Server and High Performance Computing Server [13].

6.7.2. Data parallelism

Data parallelism is inherent in program loops, which focuses on distributing the data across different computing nodes to be processed in parallel. Parallelizing loops often leads to similar operation sequences or functions being performed on elements of a large data structure. Many scientific and engineering applications exhibit data parallelism. The most commonly adopted programming language for data parallelism is Open Multi-Processors (OpenMP).

The OpenMP is a set of APIs that support multi-platform shared memory multiprocessing programming in C/C++ and FORTRAN on UNIX and Microsoft Windows platforms. It consists of a set of compiler directives, library routines, and environment variables that influence run-time behaviour. Jointly defined by a group of major computer hardware and software vendors, OpenMP is a portable, scalable model that gives programmers a simple and flexible interface for developing parallel applications for platforms ranging from the desktop to the supercomputer. An application built with the hybrid model of parallel programming can run on a computer cluster using both OpenMP and Message Passing Interface (MPI). A brief comparison of MPI and OpenMP is given in Table 1.

Table 1 Comparison of MPI and OpenMP

Criteria	OpenMP	MPI
Platform	Symmetric Multiprocessing(SMP)	Both SMP and Clusters
Parallelism	Fine grain parallelism	Coarse grain parallelism
Performance	Better on SMP	Better on Cluster

With OpenMP computation loops are often parallelized by using compiler directives, so the code runs in serial until it reaches the parallelized loop where concurrent computation is taking place. Conversely, with MPI the entire code is launched on each computing node and computing task is designated to the node by using MPI communication methods and APIs that are rich and flexible enough to implement various parallel computing models to distribute the computing tasks. To ensure the maximum speedup, both task and data parallelism can be mixed in a hybrid model.

6.7.3. Hybrid parallelism

A hybrid parallelism is to implement both task and data parallel computation in the same application to obtain the maximum speedup. A number of hybrid computation models [14] have been compared and summarized as follows.

1) Pure MPI: Task and data parallelisms are achieved by just using MPI library. The communications within one task process and across multiple task processes are implemented as a flat massively parallel processing (MPP) system.
2) MPI and OpenMP: Task parallelism is implemented by calling MPI communication methods across several computing nodes. Within each parallel task process, OpenMP is used for data parallelism.
3) Pure OpenMP: Based on virtual distributed shared memory systems (DSM), the application is parallelized only with shared memory directives of OpenMP.

The hybrid parallelism models offer advantages for the clusters of SMP computing nodes, but have some serious disadvantages based on mismatch problems between the hybrid programming scheme and the hybrid architecture, including:

1) With pure MPI, minimizing the inter-node communication requires that the application-domain's neighborhood-topology matches with the hardware technology. Otherwise, more data is shipped over the inner-node network instead of using the shared memory based communication within nodes. On the other hand, Pure MPI also introduces intra-node communication on the SMP nodes that can be omitted with hybrid programming.
2) With MPI and OpenMP programming, the intra-node communication overhead, introduced by pure MPI method, can be substitute by direct access to the application data structure in the shared memory. However, this programming style is not able to achieve full inter-node bandwidth on all platforms for any subset of inter-communicating threads. For instance, with manager only style, all non-communicating threads are idling. CPU time is also wasted, if all CPUs are already able to saturate the inter-node bandwidth. With hybrid manager only programming, additional overhead is induced by all OpenMP synchronization, but also by additional cache flushing between the generation of data in parallel regions and the consumption in subsequent message passing routines and calculations in subsequent parallel sections.
3) Overlapping of communication and computation is a chance for an optimal usage of the hardware, but it causes serious programming effort in the application itself, in OpenMP parallelization and load balancing.
4) Although pure OpenMP is simple and runs efficiently in shared-memory multiprocessor platforms, its scalability is limited by memory architecture.

Different programming schemes on clusters of SMPs show different performance benefits or penalties on the hardware platform. In order to obtain the best performance results, we have to choose the schemes bases on both the hardware and computer algorithm. In the project of pump scheduling optimization, we choose the latest release of MPICH2 as our parallel computation interface. It is also readily compatible with MSMPI supported by Microsoft Window Server 2008 and its High Performance Computing Server.

6.8. Darwin Optimization Architecture

Darwin optimization framework is based on fast messy Genetic Algorithm (fmGA) [15], [16] solver, which has been developed and applied to a number of optimization modeling tools including Darwin Calibrator [17], Darwin Designer [18] and Darwin Scheduler [19] for water distribution optimization. These applications employ the same solver of fmGA and share the similar architecture. fmGA optimization solver is decoupled from the specific applications and developed as a generic, scalable and extensible optimization solver. The common optimization solver is further generalized and implemented as parallel optimization framework.

The optimization framework is developed to meet the following criteria.

1) Generic Framework: The framework provides an architecture which has a strong decoupling between the problem definition and the framework. The framework can be used to solve any optimization problem.
2) Parallel Architecture: The framework provides application independent from the parallel optimization framework. All the parallel computation is done inside the framework. User needs minimum knowledge about parallel computing.
3) Framework User Interface: In addition a generic parallel framework, it also has a generic user interface which allows a user to set all the optimization controls. The user interface also provides a runtime optimization updates to the user.

6.8.1. Parallel computation model

A manager/worker model, as shown in Figure 7.5, is implemented for parallel genetic optimization. After GA initialization, manager process sends chromosomes to worker processes where EPS and fitness calculation is performed for solution evaluation. Then manager process collects the fitness value of chromosomes from worker processes. The manager process is also responsible for GA operations (selection and reproduction) to search for the optimal chromosome based on the searching criteria. A task parallelism model is implemented over a cluster of computers or processes so that we can greatly enhance our computation capability while making the best use of computer resources. MPI is employed as the communication API among computers. The communication and computation scope for manager/worker task parallelism is as follows.

1) Manager process sends chromosomes to worker processes for evaluation.
2) Worker process performs solution evaluation.
3) Worker processes sends the fitness value back to manager process.
4) Manager process searches for the optimal chromosome based on fitness value.

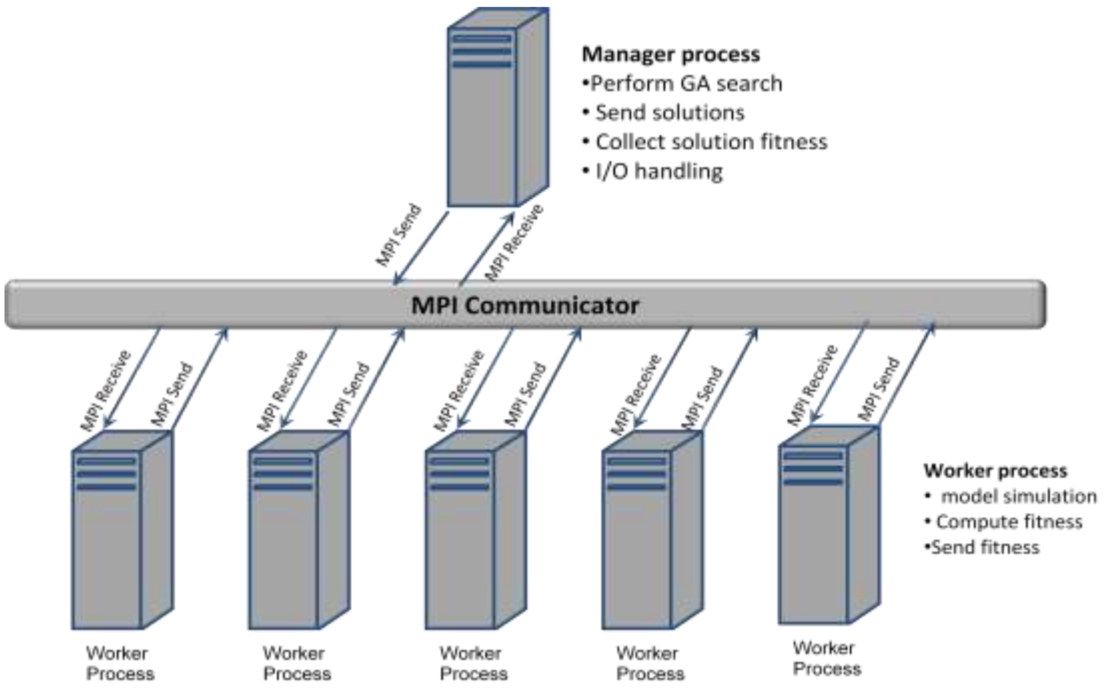


Figure 7.5 Manager-worker Parallel Computation Model

6.8.2. Framework Architecture

The parallel optimization framework is designed and implemented as shown in Figure 7.5.

MPI is employed for high-performance, easy-to-use implementation of the framework. It provides support for all of the .NET languages, and offers significant extensions, such as automatic serialization of objects, so that it makes far easier to build parallel programs. The framework is desired to have the following characteristics.

1) Generalized Parallel Executable and decoupled GAEngine. All the parallel computation is done in the Generic Parallel Executable. The GAEngine is the dynamically linked library (DLL) that comprises fmGA library. The DLL is readily extensible to incorporate other optimization methods.
2) Thin Client UI. The Thin client UI uses the framework to start the optimization solver. It specifies the input file to define decision variables and the number of processes to run the application in parallel. It is responsible for starting the generalized parallel executable using *mpiexec*.
3) User defined DLL. The framework allows a user to specify the objective functions and the constraints based on what the problem is. This is achieved using a user defined DLL. This DLL defines the objective functions and the constraints. It accepts the decision variables from the parallel executable and returns the objective function values and the constraints back to the framework.

4) Highly decoupled architecture. As depicted in the Figure 7.6, there is a clear decoupling between the client application and the framework. It is separated mainly using the input for problem definition and the User Defined DLL for objectives and the constraints.

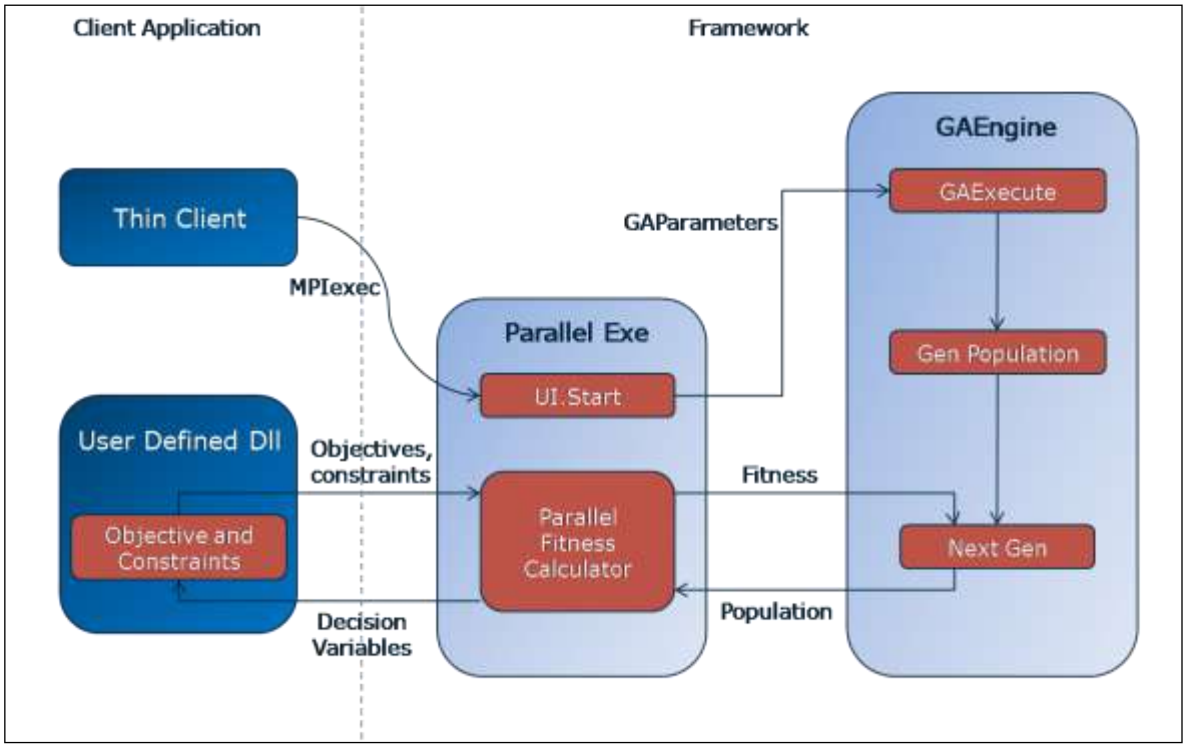


Figure 7.6 Architecture overview of parallel optimization framework

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the parallel executable and returns the objective function values and the constraints back to the framework.

8) Highly decoupled architecture. As depicted in the Figure 7.6, there is a clear decoupling between the client application and the framework. It is separated mainly using the input for problem definition and the User Defined DLL for objectives and the constraints.

The optimization framework is carefully designed and implemented in sequential and parallel computing platform for high performance analysis. It is highly decoupled from application domains and enables developers to rapidly implementing their optimization problems.

6.9. Summary

The parallel optimization framework was first applied to pump scheduling for water distribution system. Wu and Zhu [20] demonstrated significant speedup of computation time when comparing the sequential and parallel optimization of pump operation. Subsequently, the parallel optimization framework has been applied to a number of areas including architectural geometry design optimization [21], finite element model identification or calibration and structural damage detection for structure health monitoring [22], [23], and building performance-based design optimization [24]. Finally, the parallel optimization framework also serves as backbone computation engine for high performance cloud computing platform [25]. Various applications illustrate that the parallel optimization framework is robust and effective at high performance analysis for civil infrastructure system analysis.

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