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COMPARACIÓN DE Q-LEARNING Y SARSA EN LA SELECCIÓN DE ESQUEMAS DE BINARIZACIÓN PARA LA RESOLUCIÓN DE PROBLEMAS COMBINATORIALES.

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Context

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Why solve combinatorial optimization problems?

Context

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Why apply metaheuristics to solve combinatorial optimization problems?

Context

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Why apply metaheuristic binarization techniques?

Context

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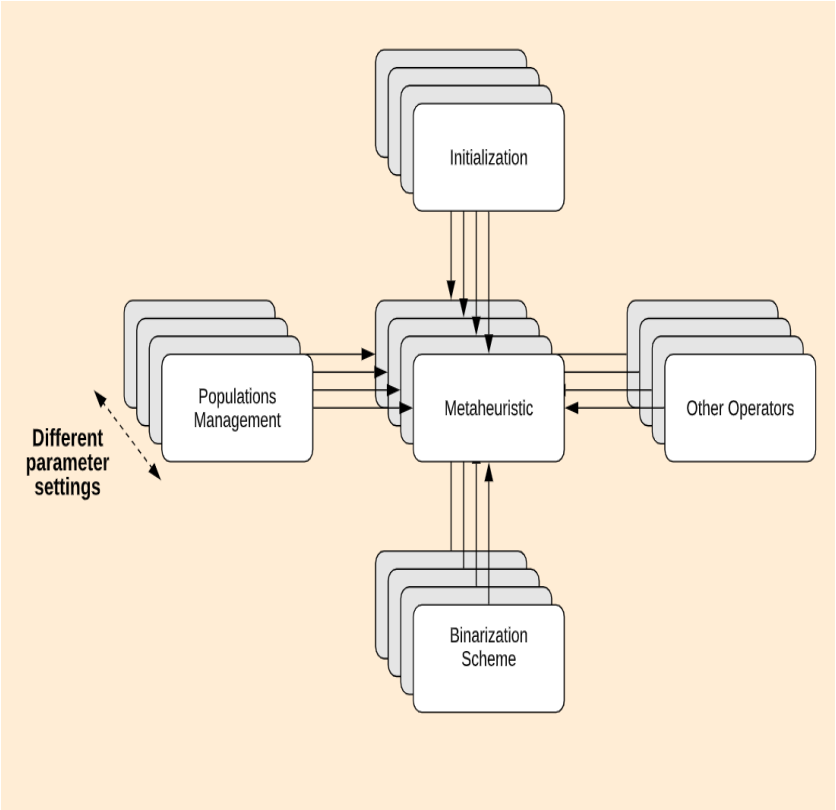
Why apply a smart selector?

Main Objective

- Develop a framework that compiles various reinforcement learning techniques in swarm-based metaheuristics by selecting binarization schemes to solve combinatorial problems. In turn, making different adjustments, such as reward functions, operators and metrics.



Specific Objectives

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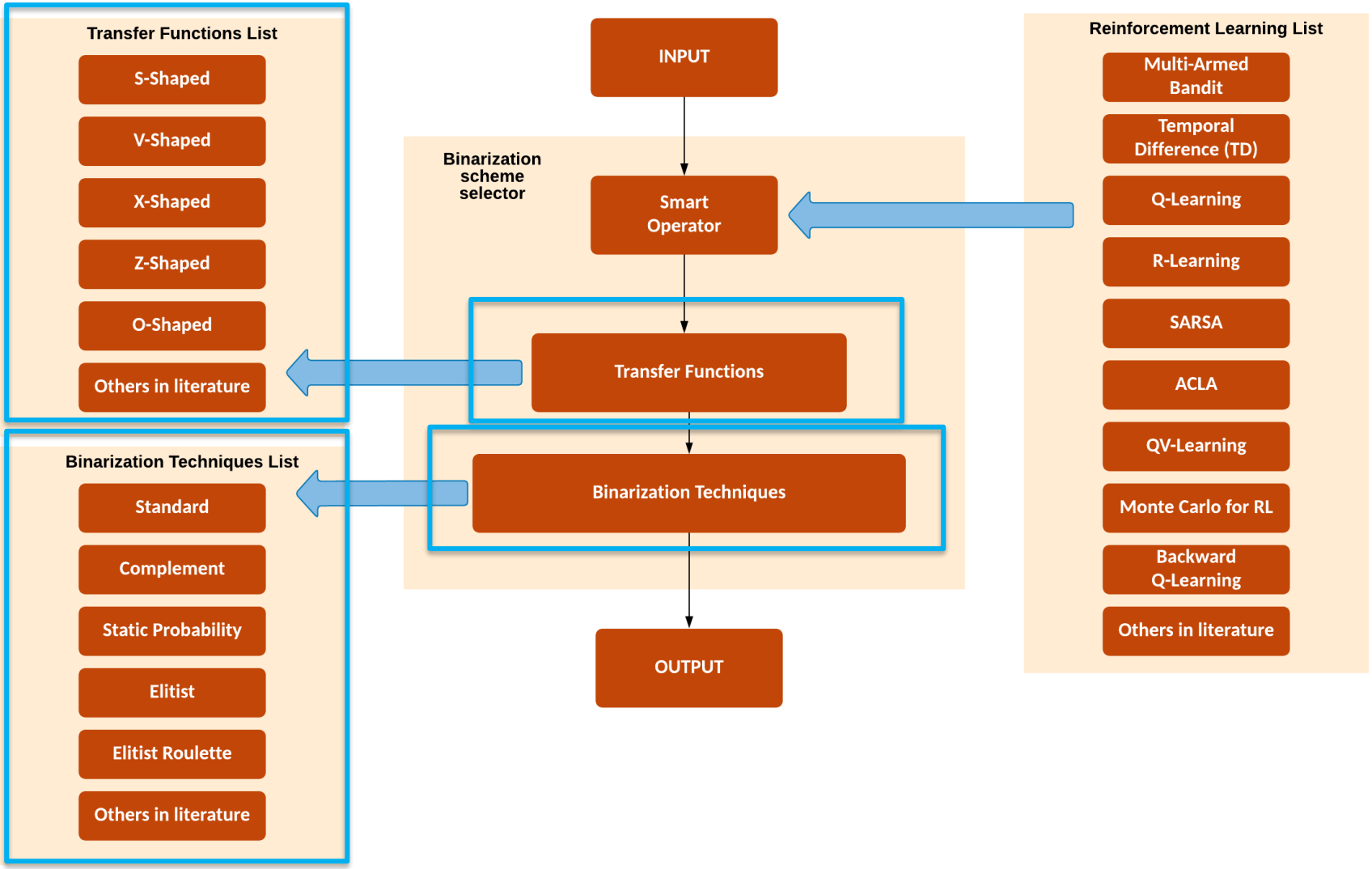
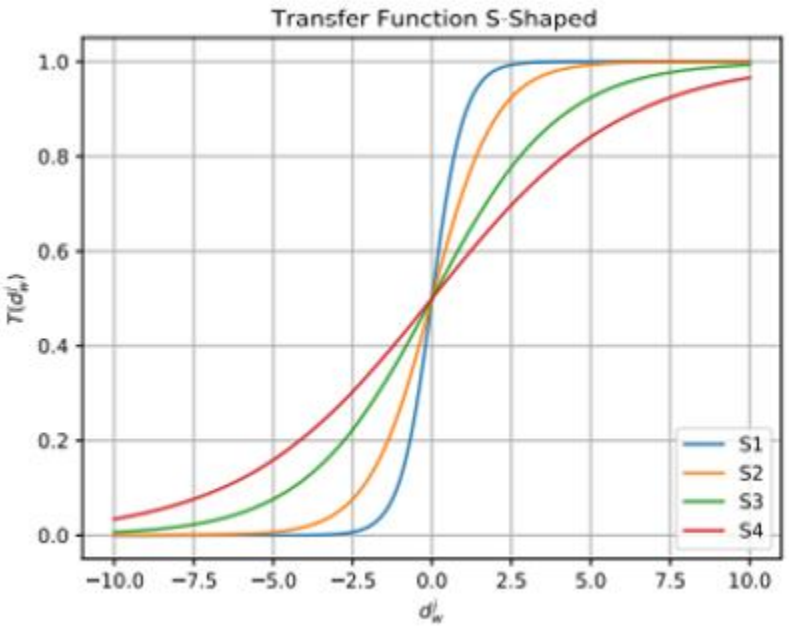
- Generate a collection of techniques to improve the solution quality of swarm-based metaheuristics when solving combinatorial problems.
- Implement various reinforcement learning techniques in swarm-based metaheuristics that allow autonomous selection of binarization schemes.
- Compare the results of the different techniques implemented and demonstrate the quality of their solutions.

Proposal


Transfer Functions List
S-Shaped
V-Shaped
X-Shaped
Z-Shaped
O-Shaped
Others in literature
Binarization Techniques List
Standard
Complement
Static Probability
Elitist
Elitist Roulette
Others in literature
INPUT
Binarization scheme selector
Smart Operator
Transfer Functions
Binarization Techniques
OUTPUT
Reinforcement Learning List
Multi-Armed Bandit
Temporal Difference (TD)
Q-Learning
R-Learning
SARSA
ACLA
QV-Learning
Monte Carlo for RL
Backward Q-Learning
Others in literature

S-Shaped



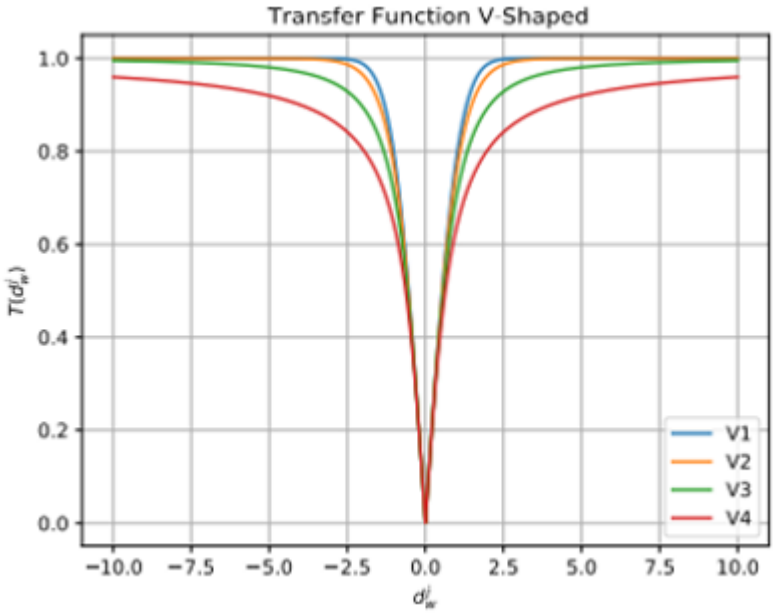
S1 $$T(d_w^j) = \frac{1}{1+e^{-2d_w^j}}$$

S2 $$T(d_w^j) = \frac{1}{1+e^{-d_w^j}}$$

S3 $$T(d_w^j) = \frac{1}{1+e^{\frac{-d_w^j}{2}}}$$

S4 $$T(d_w^j) = \frac{1}{1+e^{\frac{-d_w^j}{3}}}$$

V-Shaped



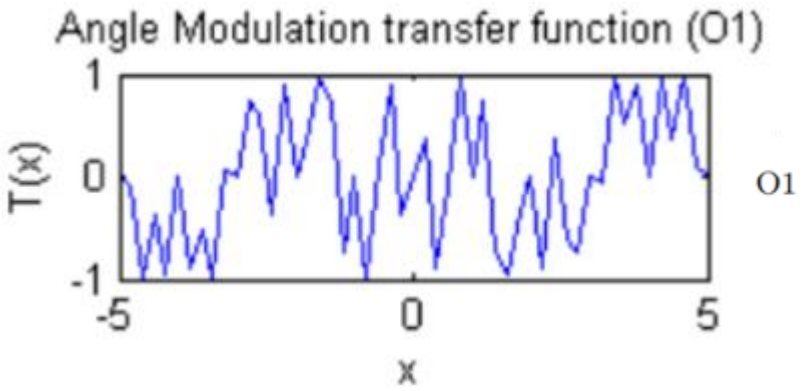
V1 $$T(d_w^j) = \left| erf\left(\frac{\sqrt{\pi}}{2} d_w^j\right) \right|$$

V2 $$T(d_w^j) = \left| tanh(d_w^j) \right|$$

V3 $$T(d_w^j) = \left| \frac{d_w^j}{\sqrt{1+(d_w^j)^2}} \right|$$

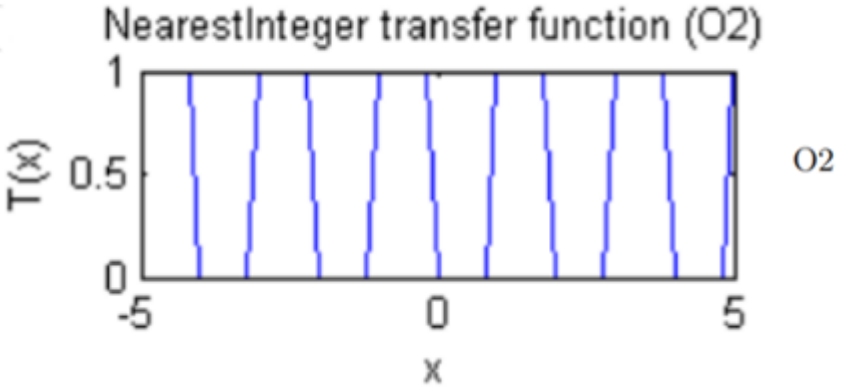
V4 $$T(d_w^j) = \left| \frac{2}{\pi} arctan\left(\frac{\pi}{2} d_w^j\right) \right|$$

O-Shaped



O1

$$T(d_w^j) = sin(2 \cdot \pi(x-a) \cdot b \cdot cos(2 \cdot \pi(x-a) \cdot c)) + d$$
$$a = 0, b = 1, c = 1, d = 0$$



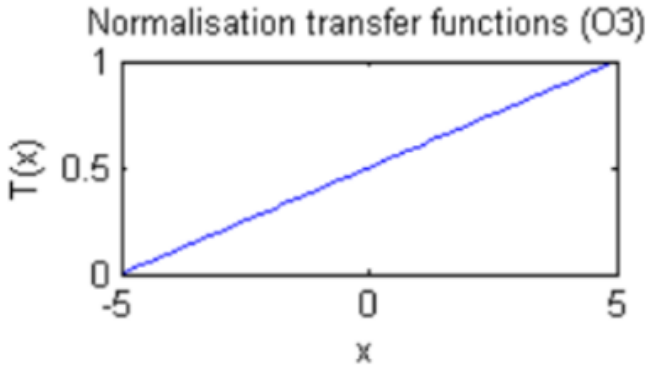
O2

$$\mathrm{T}(\mathrm{d}_w^j) = \lfloor |xmod2| \rfloor$$

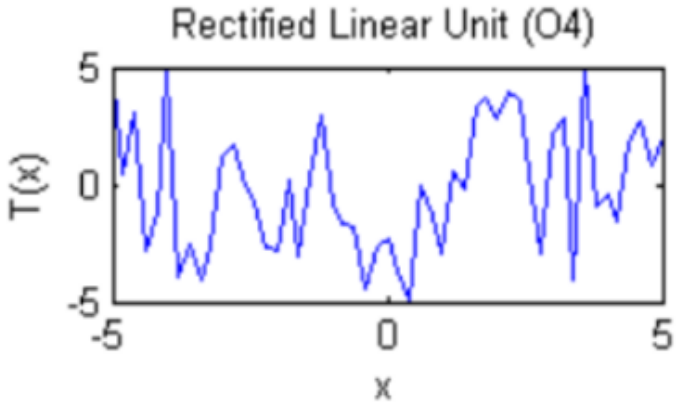
Pampara, G., Franken, N., & Engelbrecht, A. P. (2005, September). **Combining particle swarm optimisation with angle modulation to solve binary problems.**

Costa, M. F. P., Rocha, A. M. A., Francisco, R. B., & Fernandes, E. M. (2014). **Heuristic-based firefly algorithm for bound constrained nonlinear binary optimization**.

O-Shaped



O3 $\quad T(d_w^j) = \frac{(d_w^j + d_{wmin}^j)}{(|d_{wmin}^j| + d_{wmax}^j)} \quad (d_{wmin}^j \leq d_w^j \leq d_{wmax}^j)$

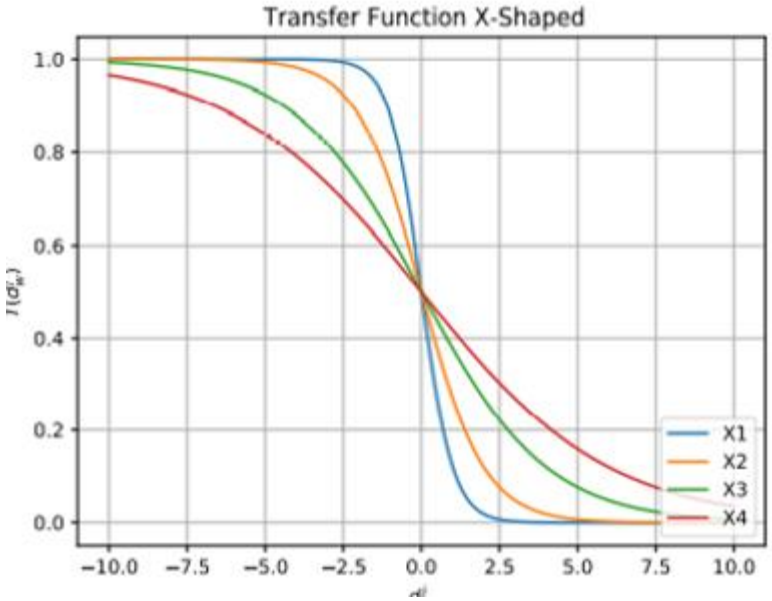


O4 $\quad T(d_w^j) = d_w^j$

Pampará, G., & Engelbrecht, A. P. (2011, April). **Binary artificial bee colony optimization.**

Zhu, H., He, Y., Wang, X., & Tsang, E. C. (2017). **Discrete differential evolutions for the discounted {0-1} knapsack problem.**

X-Shaped



X1 $$T(d_w^j) = \frac{1}{1+e^{2d_w^j}}$$

X2 $$T(d_w^j) = \frac{1}{1+e^{d_w^j}}$$

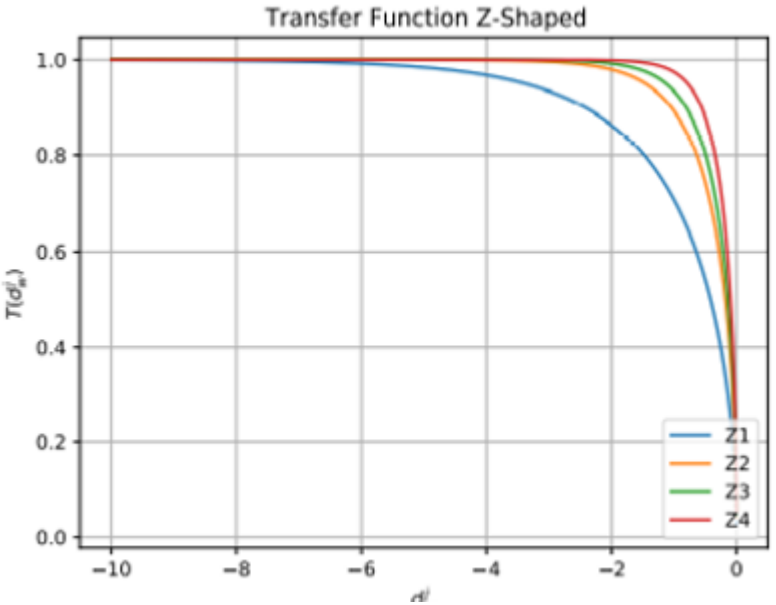
X3 $$T(d_w^j) = \frac{1}{1+e^{\frac{d_w^j}{2}}}$$

X4 $$T(d_w^j) = \frac{1}{1+e^{\frac{d_w^j}{3}}}$$

Ghosh, K. K., Singh, P. K., Hong, J., Geem, Z. W., & Sarkar, R. (2020). **Binary social mimic optimization algorithm with x-shaped transfer function for feature selection.**

Beheshti, Z. (2021). **A novel x-shaped binary particle swarm optimization.**

Z-Shaped



Z1 $$T(d_w^j) = \sqrt{1 - 2^{d_w^j}}$$

Z2 $$T(d_w^j) = \sqrt{1 - 5^{d_w^j}}$$

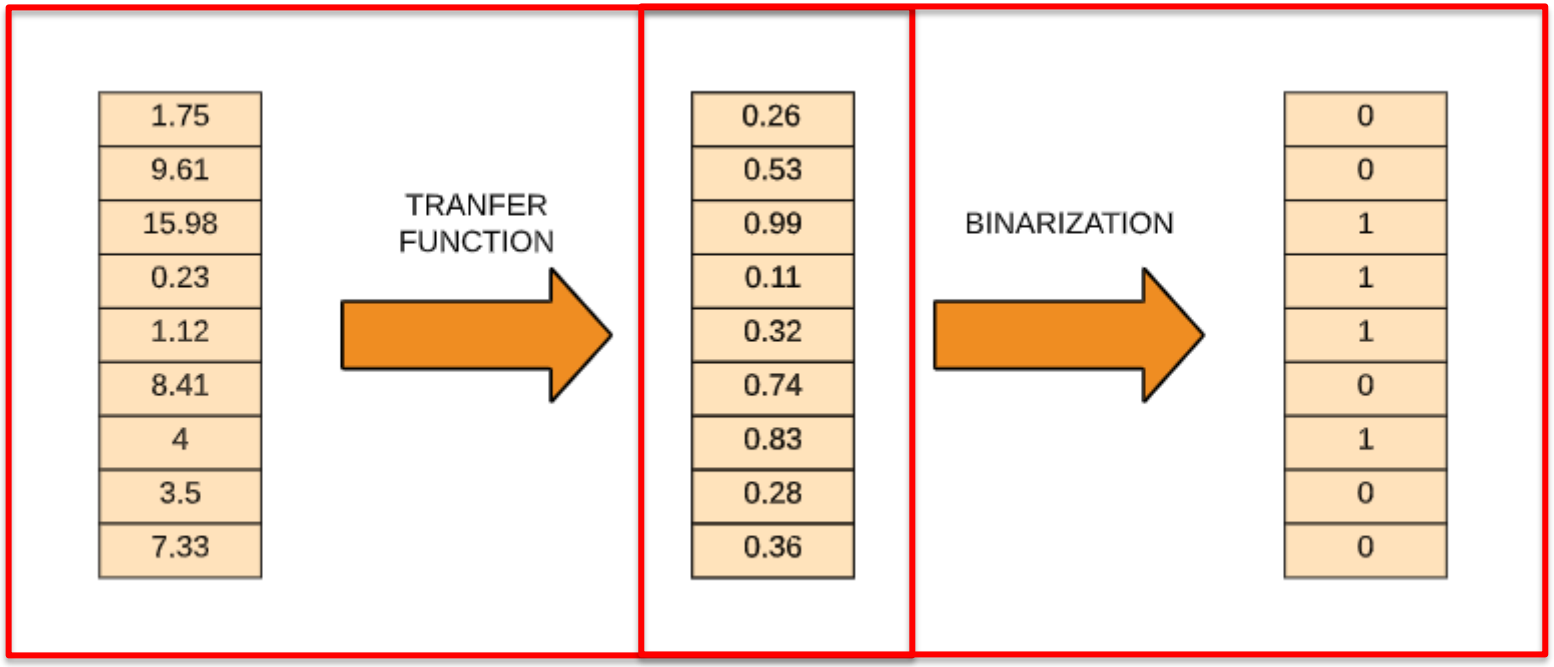
Z3 $$T(d_w^j) = \sqrt{1 - 8^{d_w^j}}$$

Z4 $$T(d_w^j) = \sqrt{1 - 20^{d_w^j}}$$

Guo, S. S., Wang, J. S., & Guo, M. W. (2020). **Z-shaped transfer functions for binary particle swarm optimization algorithm.**

Sun, W. Z., Zhang, M., Wang, J. S., Guo, S. S., Wang, M., & Hao, W. K. (2021). **Binary Particle Swarm Optimization Algorithm Based on Z-shaped Probability Transfer Function to Solve 0-1 Knapsack Problem.**

Binarization Scheme



Binarization Technique

Type	Binarization
Standard	$X^j_{new} = \begin{cases} 1 & if\ rand \leq T(d^j_w) \\ 0 & else. \end{cases}$
Complement	$X^j_{new} = \begin{cases} X^j_w & if\ rand \leq T(d^j_w) \\ 0 & else. \end{cases}$
Static Probability	$X^j_{new} = \begin{cases} 0 & if\ T(d^j_w) \leq \alpha \\ X^j_w & if\ \alpha < T(d^j_w) \leq \frac{1}{2}(1+\alpha) \\ 1 & if\ T(d^j_w) \geq \frac{1}{2}(1+\alpha) \end{cases}$
Elitist	$X^j_{new} = \begin{cases} X^j_{Best} & if\ rand < T(d^j_w) \\ 0 & else. \end{cases}$
Elitist Roulette	$X^j_{new} = \begin{cases} P[X^j_{new} = \zeta_j] = \frac{f(\zeta)}{\sum_{\delta \in Q_g} f(\delta)} & \text{if rand } \leq T(d^j_w) \\ P[X^j_{new} = 0] = 1 & else. \end{cases}$

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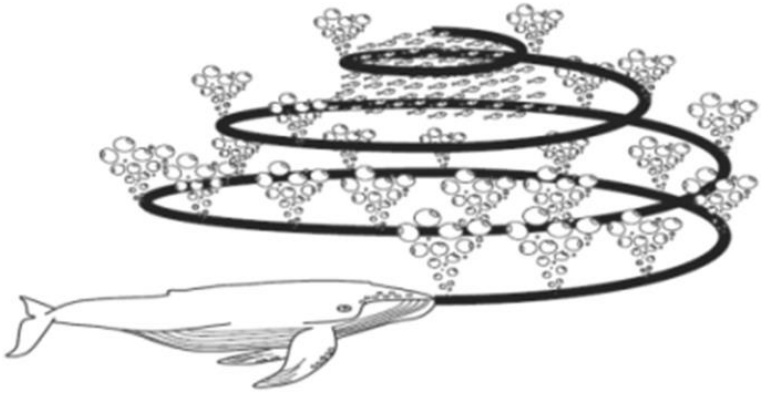
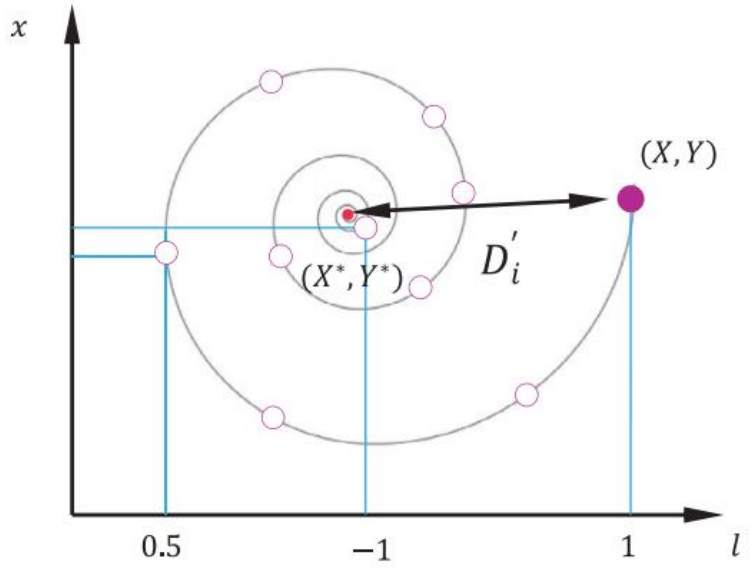
Metaheuristics implemented

Whale Optimization Algorithm (WOA)

It is a population-based metaheuristic that is inspired by the behavior of groups of whales, which have a particular hunting strategy based on bubbles.

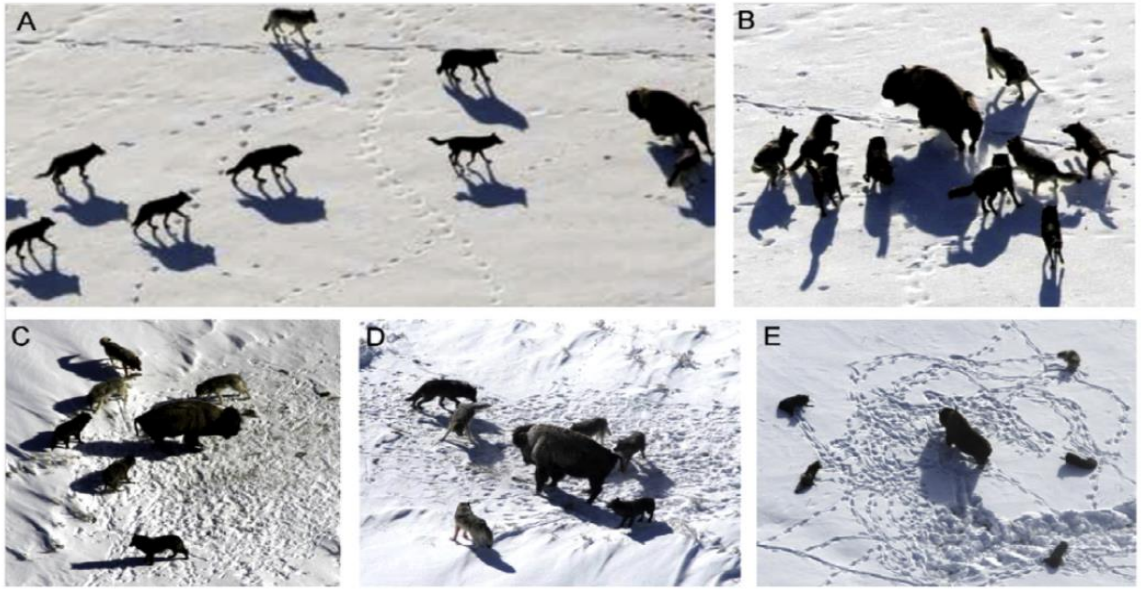




Mirjalili, S., & Lewis, A. (2016). **The whale optimization algorithm.**

Grey Wolf Optimization (GWO)

It is a population-based metaheuristic that is inspired by the behavior of gray wolves and their hierarchy when searching for and hunting their prey.

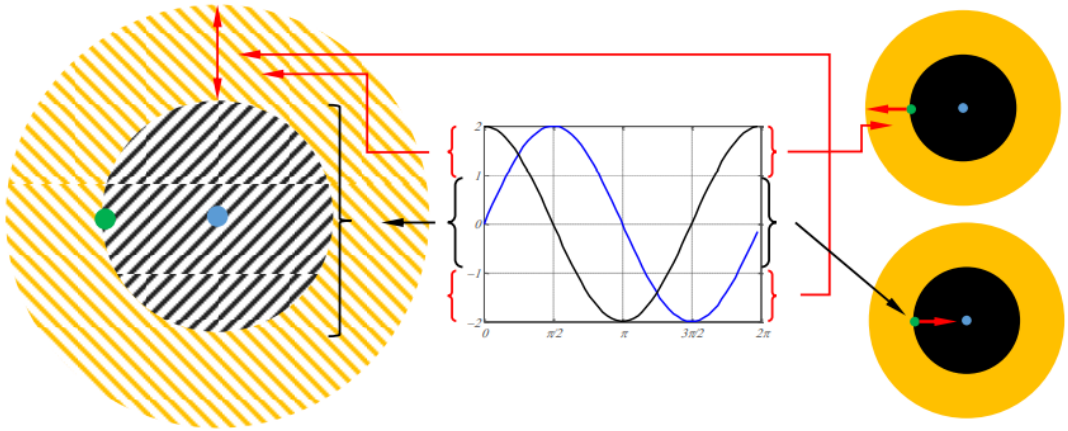


A. Pursuit, approach and tracking
B-C-D. Tracking, harassing and encircling.
E. Atack

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). **Grey wolf optimizer.**

Sine-Cosine Algorithm (SCA)

Population-based metaheuristic inspired by the fluctuation that solutions have when following a mathematical model based on sine and cosine functions.



Sine and cosine with the range in [-2,2] allow a solution to go around (inside the space between them) or beyond (outside the space between them) the destination

Mirjalili, S. (2016). **SCA: a sine cosine algorithm for solving optimization problems.**

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Machine Learning

Q-Learning Equation

Select the maximum action

$$Q_n(s_t, a_t) = Q_{n-1}(s_{t-1}, a_{t-1}) + \alpha[r_n + \gamma \cdot \max_a Q_{n+1}(s_{t+1}, a_{t+1}) - Q_n(s_t, a_t)]$$

Previous value

- Learning factor(α):
  - Indicates the importance of the information previously obtained.
  - $\alpha \in (0,1)$
- Reward(r_n):
  - Indicates the penalty or reward value of the action.
  - $r_n \in \mathbb{R}$
- Discount factor(γ):
  - It functions as a scaling factor to reward or punish in the current action.
  - $\gamma \in (0,1)$

SARSA Equation

Discount factor

$$Q_n(s_t, a_t) = Q_{n-1}(s_{t-1}, a_{t-1}) + \alpha[r_n + \gamma \cdot Q_{n+1}(s_{t+1}, a_{t+1}) - Q_{n-1}(s_{t-1}, a_{t-1})]$$

Previous Value — Reward — Value of the following state

- Learning factor(α):
  - Indicates the importance of the information previously obtained.
  - $\alpha \in (0,1)$
- Reward(r_n):
  - Indicates the penalty or reward value of the action.
  - $r_n \in \mathbb{R}$
- Discount factor(γ):
  - It functions as a scaling factor to reward or punish in the current action.
  - $\gamma \in (0,1)$

Backward Q-Learning

- It is a structure where the action is directly affected, while the policy is indirectly affected.
- Improve the speed of learning.
- Increse the precise knowledge.

$$Q_n(s_t^i, a_t^i) = Q(s_t^i, a_t^i) + \alpha[r_{t+1}^i + \gamma \cdot maxQ(s_t^i, a_t^i) - Q(s_t^i, a_t^i)]$$

$$Q_n(s_t^j, a_t^j) = Q(s_t^j, a_t^j) + \alpha[r_{t+1}^j + \gamma \cdot maxQ(s_t^j, a_t^j) - Q(s_t^j, a_t^j)]$$

$$j = N, N-1, N-2, \ldots, 1.$$

$$M^i \leftarrow s_t^i, a_t^i, r_t^i, s_{t+1}^i$$

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Problems to be solved

Set Covering Problem (SCP)

SCP aims to minimize the cost of the subset S ⊆ J, with the constraint that all rows i ∈ I are covered by at least one column j ∈ J. Note that when column j is in the subset of solutions S, this is equal to 1, otherwise it corresponds to a 0.

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix}$$

Mathematical model

Objective Function :

$$Minimize\ Z = \sum_{j=1}^{n} c_j \cdot x_j$$

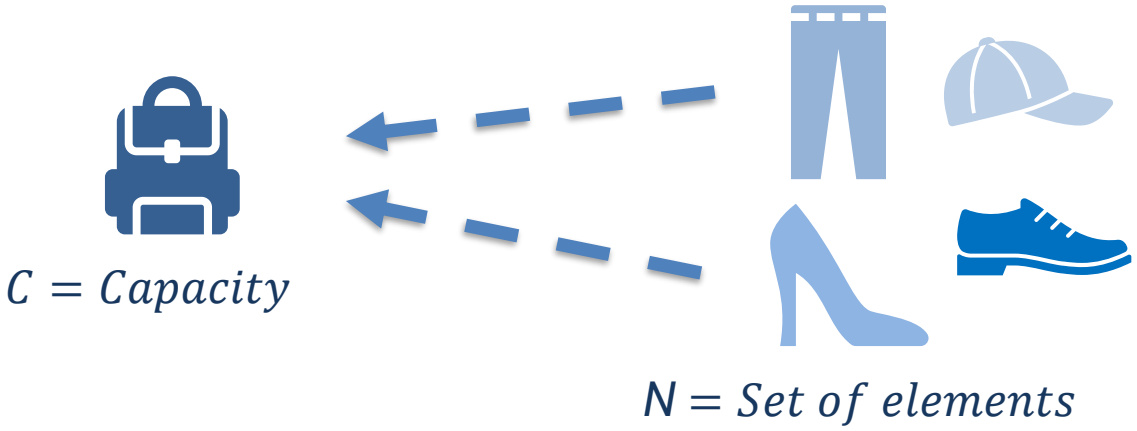
Subject to:

$$\sum_{j=1}^{n} a_{i,j} \cdot x_j, \quad \forall i \in I = \{1, 2, 3, ..., m\}$$

$$x_j \in \{0, 1\}, \quad \forall j \in J = \{1, 2, 3, ..., n\}$$

Knapsack Problem (KP)

It is classified as an NP-hard problem. Where it is assumed that there is a knapsack with a maximum capacity C and a set of elements N. Composed by each object element having a value p_i and a weight w_i. Where we seek to maximize the value of objects stored in the backpack, without exceeding the maximum capacity C.



Mathematical model

Objective Function :

$$Maximize \quad \sum_{i=1}^{n} p_i$$

Subject to :

$$\sum_{i=1}^{n} w_i \leq C$$

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Experimental Results

Diversity Determination

$$\text{Div} = \frac{1}{\text{l} \cdot \text{n}} \sum_{d=1}^{l} \sum_{i=1}^{n} |\bar{x}^d - x_i^d|$$

Where:

- Div: Diversity status determination
- $\bar{x}^d$: denotes the mean of the individuals in dimension d.
- x_i^d: is the value of the i-th individual of the d-th dimension.
- n: is the number of individuals in the population
- l: is the size of the dimensión of the individuals

Hussain, K., Zhu, W., & Salleh, M. N. M. (2019). **Long-term memory Harris' hawk optimization for high dimensional and optimal power flow problems.**

State Determination

$$XPL\% = \frac{Div}{Div_{max}} \cdot 100, \qquad if\ XPL\% \leq 50\%$$

$$XPLT\% = \frac{|Div - Div_{max}|}{Div_{max}} \cdot 100, \qquad if\ XPLT\% > 50\%$$

Where:

- Div : is the diversity calculated above
- Div_{max}: denotes the maximum value of the diversity state found in the whole optimization problem.

Morales-Castañeda, B., Zaldivar, D., Cuevas, E., Fausto, F., & Rodríguez, A. (2020). **A better balance in metaheuristic algorithms: Does it exist?.**

Implementation rewards

Name of Reward	Mathematical Formula
With Penalty	$r_n = \begin{cases} +1, & \text{If fitness improves} \\ -1, & \text{Otherwise} \end{cases}$
Without Penalty	$r_n = \begin{cases} +1, & \text{If fitness improves} \\ 0, & \text{Otherwise} \end{cases}$
Global Best	$r_n = \begin{cases} \frac{W}{BestFitness}, & \text{If fitness improves} \\ 0, & \text{Otherwise} \end{cases}$
Root Adaption	$r_n = \begin{cases} \sqrt{BestFitness}, & \text{If fitness improves} \\ 0, & \text{Otherwise} \end{cases}$
Scalating Adaption	$r_n = \begin{cases} W \cdot BestFitness, & \text{If fitness improves} \\ 0, & \text{Otherwise} \end{cases}$

Nareyek A. (2003). **Choosing search heuristics by non-stationary reinforcement learning.**

Implementation rewards (IDs)

Reward Types	Name
With Penalty	SA1 QL1 BQSA1
Without Penalty	SA2 QL2
Global Best	SA3 QL3
Root Adaption	SA4 QL4
Scalating Adaption.	SA5 QL5

Binarization	Transfer Function	Name
Elitist	V4	BCL
Complement	V4	MIR

Lanza-Gutierrez, J. M., Crawford, B., Soto, R., Berrios, N., Gomez-Pulido, J. A., & Paredes, F. (2017). **Analyzing the effects of binarization techniques when solving the set covering problem through swarm optimization.**
Mirjalili, S., & Lewis, A. (2013). **S-shaped versus V-shaped transfer functions for binary particle swarm optimization.**

Summary table – SCP with 85 actions

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	WOA							
	BCL		MIR		QL1		SA1	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	490.31	178.89	1195.82	787.64	264.84	4.37	**263.84**	4.02
	GWO							
	BCL		MIR		QL1		SA1	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	**260.11**	2.42	272.22	11.75	266.91	5.45	265.04	4.83
	SCA							
	BCL		MIR		QL1		SA1	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	305.56	20.45	1123.22	728.24	266.27	4.9	**265.33**	4.59

Summary table – SCP with 40 actions

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	WOA					
	BCL		MIR		BQSA1	
	Best	RPD	Best	RPD	Best	RPD
$\sum$	490.31	178.89	1195.82	787.64	**266.71**	5.08
	GWO					
	BCL		MIR		BQSA1	
	Best	RPD	Best	RPD	Best	RPD
$\sum$	**260.11**	2.42	272.22	11.75	268.6	6.19
	SCA					
	BCL		MIR		BQSA1	
	Best	RPD	Best	RPD	Best	RPD
$\sum$	305.56	20.45	1123.22	728.24	**268.02**	5.99

Summary table – 0-1KP

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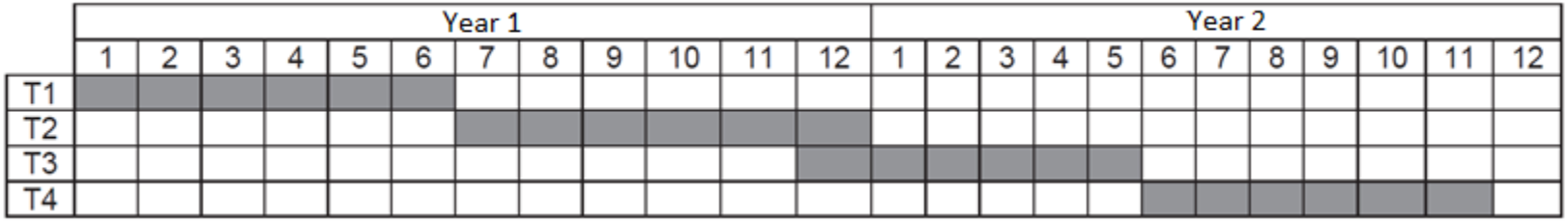
	WOA									
	SA1		**SA2**		**SA3**		**SA4**		**SA5**	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	2347.0	17.7	2329.06	17.81	2282.16	18.16	2324.79	18.35	2330.64	17.73
	QL1		**QL2**		**QL3**		**QL4**		**QL5**	
	Best	RPD	Best	RPD	Best	RPD	Best	Avg	Best	RPD
∑	**2410.42**	17.22	2390.95	17.46	2343.85	18.04	2304.11	18.18	2381.16	17.54
	GWO									
	SA1		**SA2**		**SA3**		**SA4**		**SA5**	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	**2570.37**	15.21	2567.32	15.16	2566.32	15.15	2538.74	15.39	2545.42	15.35
	QL1		**QL2**		**QL3**		**QL4**		**QL5**	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	2560.74	14.98	2477.0	16.11	2488.53	16.22	2502.0	16.0	2486.64	16.05
	SCA									
	SA1		**SA2**		**SA3**		**SA4**		**SA5**	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	**2417.0**	17.17	2323.79	17.79	2315.58	17.98	2348.42	17.77	2326.37	17.95
	QL1		**QL2**		**QL3**		**QL4**		**QL5**	
	Best	RPD	Best	RPD	Best	RPD	Best	RPD	Best	RPD
∑	2384.06	17.31	2344.0	17.85	2344.74	17.61	2335.27	17.87	2343.74	17.97

Work Plan

- T1: **Review existing literature** regarding ML techniques improving continuous swarm intelligence MH, binarization techniques and transfer functions.
- T2: **Implement** more transfer functions and binarization techniques, increasing the number of options to choose from with the smart selector.
- T3: **Implement** further ML techniques for binarization scheme selection in a continuous swarm intelligence MH.
- T4: **Perform** experiments and comparisons of the implementations against results of other continuous swarm intelligence MH techniques present in the state of the art, solving combinatorial problems.



Thesis proposal for the next two years

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- **WP1: First Semester**
  - Search more T.F and B.T in the literature (SLR in progress).
  - Search the literature for other possible intelligent selectors.
  - Drafting and submitting an SLR
  - Test the feasibility of comparing Binary Measures Similarity with our way of assessing diversity.
- **WP2: Second Semester**
  - Algorithmic complexity calculation and description of the software architecture used
  - Implement more transfer functions and binarization techniques.
  - Drafting and submitting an article with BQSA and 85 actions.
- **WP3: Third Semester**
  - Implement the Multi-armed Bandit.
  - Implement some technique from the ML literature for the selection of binarization schemes.
  - Search for new ways to represent the data obtained from the experiments.
- **WP4: Fourth Semester**
  - Obtain all necessary results.
  - Obtain all necessary graphics.
  - Obtain all necessary comparisons.
  - Drafting and submitting an article with Mutil-armed Bandit.

Participation in previous projects

PONTIFICIA UNIVERSIDAD CATÓLICA DE VALPARAÍSO

- Assistant of the research project DI Investigación Interdisciplinaria del Pregrado 2021. **Q-learnheuristics de enjambre para la resolución de problemas combinatoriales.**
- Assistant of the research project Núcleos de Investigación PUCV - Renovación 2021. **Data Analytics.**
- Assistant of the research project DI Investigación Interdisciplinaria del Pregrado 2020. **Metaheurísticas balanceadas guiadas por datos.**
- Assistant of the research Project DIE – Tesis Innovadoras 2020**. MHSolver – Inteligencia Artificial Aplicada a la Optimización de Procesos Logísticos.**
- Assistant of research Project CONICYT/FONCEDYT Regular Nº 1210810. **Data-driven ambidextrous metaheuristics: using machine learning approaches to manage balance of exploration and exploitation when solving combinatorial problems with continuous swarm intelligence algorithm. 2020 – To present.**

Previous works and Publications

- Lemus-Romani, J., Becerra-Rozas, M., Crawford, B., Soto, R., Cisternas-Caneo, F., Vega, E., ... & García, J. (2021). **A Novel Learning-Based Binarization Scheme Selector for Swarm Algorithms Solving Combinatorial Problems. (WoS) (Q1)**
- Crawford, B., Soto, R., de la Fuente Mella, H., Elortegui, C., Palma, W., Torres-Rojas, C., Vasconcellos-Gaete, C., Becerra-Rozas, M., Peña, J. & Misra, S. (In proceeding) **Binary Fruit Fly Swarm Algorithms for the Set Covering Problem. (WoS)(Q2)**
- Crawford, B., Soto, R., Lemus-Romani, J., Becerra-Rozas, M., Lanza-Gutiérrez, J. M., Caballé, N., ... & Rubio, J. M. (2021**). Q-learnheuristics: Towards data-driven balanced metaheuristics. (WoS)(Q1)**
- García, J., Lemus-Romani, J., Altimiras, F., Crawford, B., Soto, R., Becerra-Rozas, M., ... & Astorga, G. (2021). **A binary machine learning cuckoo search algorithm improved by a local search operator for the set-union knapsack problem. (WoS) (Q1)**
- Becerra-Rozas, M., Lemus-Romani, J., Crawford, B., Soto, R., Cisternas-Caneo, F., Embry, A. T., ... & Rubio, J. M. (In proceeding) **A New Learnheuristic: Binary SARSA - Sine Cosine Algorithm (BS-SCA) (Scopus)**
- Becerra-Rozas, M., Lemus-Romani, J., Crawford, B., Soto, R., Cisternas-Caneo, F., Embry, A. T., ... & Rubio, J. M. (2021, September). **Reinforcement Learning Based Whale Optimizer. (Scopus)**
- Tapia, D., Crawford, B., Soto, R., Palma, W., Lemus-Romani, J., Cisternas-Caneo, F., ... & Misra, S. (2021, March). **Embedding Q-Learning in the selection of metaheuristic operators: The enhanced binary grey wolf optimizer case. (Scopus)**
- Cisternas-Caneo, F., Crawford, B., Soto, R., Tapia, D., Lemus-Romani, J., Castillo, M., ... & Misra, S. (2020, December). **A data-driven dynamic discretization framework to solve combinatorial problems using continuous metaheuristics. (Scopus)**
- Crawford, B., Soto, R., Cisternas-Caneo, F., Tapia, D., Palma, W., Lemus-Romani, J., ... & Becerra-Rozas, M. (2021, June). **A Comparison of Learnheuristics Using Different Reward Functions to Solve the Set Covering Problem. (Scopus)**

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A SELF-LEARNING METAHEURISTIC FRAMEWORK BASED ON REINFORCEMENT LEARNING FOR COMBINATORIAL PROBLEM

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Escuela de Ingeniería Informática
Examen de Grado - Candidatura

Valparaíso, Enero 2022

Table 13: SCP - WOA - 85 ACTIONS

Inst.	Opt.	BCL			MIR			QL1			SA1		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
41	429	542.0	583.7	26.34	683.0	713.4	59.21	438.0	438.0	2.1	434.0	434.0	1.17
42	512	756.0	809.9	47.66	1114.0	1163.8	117.58	543.0	543.0	6.05	538.0	538.0	5.08
43	516	739.0	846.9	43.22	1230.0	1264.7	138.37	539.0	539.0	4.46	538.0	538.0	4.26
44	494	596.0	739.8	20.65	954.0	1032.5	93.12	523.0	523.0	5.87	518.0	518.0	4.86
45	512	755.0	821.0	47.46	1121.0	1192.6	118.95	537.0	537.0	4.88	530.0	530.0	3.52
46	560	815.0	913.0	45.54	1391.0	1464.0	148.39	572.0	572.0	2.14	571.0	571.0	1.96
47	430	597.0	652.2	38.84	854.0	912.2	98.6	440.0	440.0	2.33	441.0	441.0	2.56
48	492	757.0	844.3	53.86	1148.0	1208.4	133.33	504.0	504.0	2.44	500.0	500.0	1.63
49	641	922.0	1031.1	43.84	1586.0	1678.7	147.43	680.0	680.0	6.08	676.0	676.0	5.46
410	514	696.0	787.2	35.41	1090.0	1153.4	112.06	528.0	528.0	2.72	527.0	527.0	2.53
51	253	378.0	398.4	49.41	582.0	607.0	130.04	260.0	260.0	2.77	262.0	262.0	3.56
52	302	502.0	542.2	66.23	804.0	879.0	166.23	330.0	330.0	9.27	328.0	328.0	8.61
53	226	320.0	363.3	41.59	506.0	547.0	123.89	233.0	233.0	3.1	231.0	231.0	2.21
54	242	318.0	366.5	31.4	540.0	566.6	123.14	251.0	251.0	3.72	251.0	251.0	3.72
55	211	305.0	327.7	44.55	397.0	417.5	88.15	217.0	217.0	2.84	217.0	217.0	2.84
56	213	358.0	379.3	68.08	531.0	540.8	149.3	226.0	227.0	6.1	224.0	224.0	5.16
57	293	387.0	475.7	32.08	642.0	703.8	119.11	306.0	306.0	4.44	305.0	305.0	4.1
58	288	422.0	468.7	46.53	673.0	732.6	133.68	297.0	297.0	3.12	296.0	296.0	2.78
59	279	430.0	495.5	54.12	698.0	728.8	150.18	284.0	284.0	1.79	286.0	286.0	2.51
510	265	429.0	455.2	61.89	594.0	655.2	124.15	273.0	273.0	3.02	273.0	273.0	3.02
61	138	285.0	356.5	106.52	752.0	818.9	444.93	144.0	144.0	4.35	144.0	144.0	4.35
62	146	413.0	509.5	182.88	1100.0	1175.9	653.42	152.0	152.0	4.11	153.0	153.0	4.79
63	145	337.0	450.9	132.41	1030.0	1099.7	610.34	149.0	149.0	2.76	147.0	147.0	1.38
64	131	286.0	327.3	118.32	655.0	704.3	400.0	134.0	134.0	2.29	133.0	133.0	1.53
65	161	357.0	429.1	121.74	1050.0	1124.6	552.17	176.0	176.0	9.32	172.0	172.0	6.83
a1	253	479.0	577.4	89.33	1243.0	1323.1	391.3	266.0	266.0	5.14	264.0	264.0	4.35
a2	252	452.0	613.1	79.37	1150.0	1211.2	356.35	267.0	267.0	5.95	266.0	266.0	5.56
a3	232	436.0	526.0	87.93	1117.0	1174.2	381.47	243.0	243.0	4.74	243.0	243.0	4.74
a4	234	469.0	558.6	100.43	1080.0	1136.9	361.54	242.0	242.0	3.42	247.0	247.0	5.56
a5	236	447.0	576.1	89.41	1139.0	1168.0	382.63	247.0	247.0	4.66	245.0	245.0	3.81
b1	69	380.0	509.0	450.72	1353.0	1407.2	1860.87	71.0	71.0	2.9	71.0	71.0	2.9
b2	76	374.0	508.2	392.11	1265.0	1372.7	1564.47	78.0	78.0	2.63	78.0	78.0	2.63
b3	80	468.0	574.8	485.0	1753.0	1808.5	2091.25	81.0	81.0	1.25	82.0	82.0	2.5
b4	79	372.0	589.4	370.89	1536.0	1616.1	1844.3	83.0	83.0	5.06	83.0	83.0	5.06
b5	72	376.0	440.5	422.22	1372.0	1441.0	1805.56	74.0	74.0	2.78	72.0	73.0	0.0
c1	227	523.0	671.9	130.4	1488.0	1581.9	555.51	242.0	242.0	6.61	243.0	243.0	7.05
c2	219	507.0	629.8	131.51	1654.0	1741.8	655.25	237.0	237.0	8.22	232.0	232.0	5.94
c3	243	629.0	759.5	158.85	2059.0	2123.0	747.33	256.0	256.0	5.35	258.0	258.0	6.17
c4	219	570.0	716.0	160.27	1645.0	1721.1	651.14	232.0	232.0	5.94	231.0	231.0	5.48
c5	215	496.0	636.9	130.7	1619.0	1684.6	653.02	226.0	226.0	5.12	227.0	227.0	5.58
d1	60	419.0	620.8	598.33	1950.0	2057.5	3150.0	64.0	64.0	6.67	64.0	64.0	6.67
d2	66	480.0	700.6	627.27	2264.0	2314.1	3330.3	69.0	69.0	4.55	68.0	68.0	3.03
d3	72	548.0	735.3	661.11	2445.0	2526.3	3295.83	77.0	77.0	6.94	77.0	77.0	6.94
d4	62	476.0	720.4	667.74	2025.0	2079.9	3166.13	63.0	63.0	1.61	63.0	63.0	1.61
d5	61	461.0	749.8	655.74	1930.0	2055.9	3063.93	64.0	64.0	4.92	64.0	64.0	4.92
		490.31	595.31	178.89	1195.82	1258.45	787.64	264.84	264.87	4.37	**263.84**	263.87	4.02

Table 15: SCP - GWO - 85 ACTIONS

Inst.	Opt.	BCL			MIR			QL1			SA1		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
41	429	432.0	433.5	0.7	431.0	434.4	0.47	433.0	433.0	0.93	434.0	434.0	1.17
42	512	533.0	539.1	4.1	543.0	547.8	6.05	538.0	538.0	5.08	537.0	537.0	4.88
43	516	527.0	532.5	2.13	541.0	546.3	4.84	544.0	544.0	5.43	532.0	532.0	3.1
44	494	507.0	514.3	2.63	513.0	520.5	3.85	516.0	516.0	4.45	512.0	512.0	3.64
45	512	523.0	528.2	2.15	540.0	549.6	5.47	543.0	543.0	6.05	542.0	542.0	5.86
46	560	570.0	579.1	1.79	579.0	583.2	3.39	577.0	577.0	3.04	573.0	573.0	2.32
47	430	434.0	437.8	0.93	442.0	445.7	2.79	443.0	443.0	3.02	439.0	439.0	2.09
48	492	499.0	506.3	1.42	509.0	512.6	3.46	507.0	507.0	3.05	503.0	503.0	2.24
49	641	656.0	671.4	2.34	685.0	690.3	6.86	682.0	682.0	6.4	681.0	681.0	6.24
410	514	520.0	525.7	1.17	528.0	531.2	2.72	528.0	528.0	2.72	524.0	524.0	1.95
51	253	260.0	265.8	2.77	264.0	266.5	4.35	266.0	266.0	5.14	263.0	263.0	3.95
52	302	322.0	328.3	6.62	326.0	333.7	7.95	329.0	329.0	8.94	326.0	326.0	7.95
53	226	230.0	233.3	1.77	232.0	234.2	2.65	234.0	234.0	3.54	233.0	233.0	3.1
54	242	247.0	249.8	2.07	250.0	253.1	3.31	252.0	252.0	4.13	248.0	248.0	2.48
55	211	212.0	213.8	0.47	216.0	217.9	2.37	218.0	218.0	3.32	217.0	217.0	2.84
56	213	216.0	223.8	1.41	222.0	228.2	4.23	227.0	227.0	6.57	222.0	224.0	4.23
57	293	299.0	306.8	2.05	309.0	311.8	5.46	311.0	311.0	6.14	308.0	308.0	5.12
58	288	290.0	296.2	0.69	297.0	300.7	3.12	298.0	298.0	3.47	296.0	296.0	2.78
59	279	282.0	285.0	1.08	285.0	293.0	2.15	289.0	289.0	3.58	285.0	285.0	2.15
510	265	269.0	275.0	1.51	277.0	280.7	4.53	278.0	278.0	4.91	275.0	275.0	3.77
61	138	140.0	145.2	1.45	144.0	148.1	4.35	146.0	146.0	5.8	145.0	145.0	5.07
62	146	147.0	152.3	0.68	155.0	158.9	6.16	155.0	155.0	6.16	154.0	154.0	5.48
63	145	147.0	149.8	1.38	151.0	151.5	4.14	150.0	150.0	3.45	150.0	150.0	3.45
64	131	131.0	134.3	0.0	134.0	135.3	2.29	134.0	134.0	2.29	134.0	134.0	2.29
65	161	167.0	172.3	3.73	175.0	183.7	8.7	173.0	173.0	7.45	174.0	174.0	8.07
a1	253	262.0	263.2	3.56	271.0	277.6	7.11	266.0	266.0	5.14	266.0	266.0	5.14
a2	252	263.0	268.1	4.37	275.0	279.2	9.13	269.0	269.0	6.75	270.0	270.0	7.14
a3	232	241.0	245.3	3.88	250.0	256.1	7.76	248.0	248.0	6.9	246.0	246.0	6.03
a4	234	244.0	247.4	4.27	250.0	257.8	6.84	252.0	252.0	7.69	243.0	243.0	3.85
a5	236	244.0	246.5	3.39	255.0	259.0	8.05	249.0	249.0	5.51	247.0	247.0	4.66
b1	69	70.0	71.1	1.45	75.0	81.5	8.7	70.0	70.0	1.45	71.0	71.0	2.9
b2	76	76.0	78.3	0.0	86.0	91.3	13.16	81.0	81.0	6.58	80.0	80.0	5.26
b3	80	81.0	82.2	1.25	89.0	98.1	11.25	84.0	84.0	5.0	82.0	82.0	2.5
b4	79	82.0	82.9	3.8	95.0	100.0	20.25	81.0	81.0	2.53	84.0	84.0	6.33
b5	72	73.0	73.5	1.39	81.0	90.5	12.5	74.0	74.0	2.78	74.0	74.0	2.78
c1	227	239.0	248.1	5.29	263.0	272.7	15.86	249.0	249.0	9.69	250.0	250.0	10.13
c2	219	233.0	238.1	6.39	260.0	265.0	18.72	240.0	240.0	9.59	240.0	240.0	9.59
c3	243	252.0	257.3	3.7	279.0	289.1	14.81	265.0	265.0	9.05	261.0	261.0	7.41
c4	219	233.0	235.7	6.39	250.0	257.9	14.16	235.0	235.0	7.31	232.0	232.0	5.94
c5	215	226.0	229.4	5.12	248.0	256.3	15.35	233.0	234.0	8.37	231.0	231.0	7.44
d1	60	62.0	63.5	3.33	83.0	98.2	38.33	65.0	65.0	8.33	65.0	65.0	8.33
d2	66	66.0	68.3	0.0	97.0	113.7	46.97	71.0	71.0	7.58	70.0	70.0	6.06
d3	72	75.0	76.4	4.17	108.0	121.6	50.0	77.0	77.0	6.94	78.0	78.0	8.33
d4	62	62.0	63.5	0.0	90.0	101.9	45.16	65.0	65.0	4.84	64.0	64.0	3.23
d5	61	61.0	64.0	0.0	97.0	106.4	59.02	66.0	66.5	8.2	66.0	66.0	8.2
		260.11	264.5	2.42	272.22	278.51	11.75	266.91	266.94	5.45	265.04	265.09	4.83

Table 17: SCP - SCA - 85 ACTIONS

Inst.	Opt.	BCL			MIR			QL1			SA1		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
41	429	526.0	577.8	22.61	689.0	707.2	60.61	440.0	440.0	2.56	435.0	435.0	1.4
42	512	600.0	720.5	17.19	1060.0	1165.8	107.03	547.0	547.0	6.84	540.0	540.0	5.47
43	516	589.0	741.6	14.15	1185.0	1269.0	129.65	541.0	541.0	4.84	538.0	538.0	4.26
44	494	580.0	709.2	17.41	986.0	1020.8	99.6	523.0	523.0	5.87	516.0	516.0	4.45
45	512	700.0	810.1	36.72	1126.0	1184.3	119.92	531.0	531.0	3.71	535.0	535.0	4.49
46	560	692.0	793.2	23.57	1421.0	1475.5	153.75	581.0	581.0	3.75	579.0	579.0	3.39
47	430	498.0	606.0	15.81	886.0	920.3	106.05	438.0	438.0	1.86	440.0	440.0	2.33
48	492	577.0	719.3	17.28	1119.0	1226.7	127.44	506.0	506.0	2.85	502.0	502.0	2.03
49	641	779.0	918.0	21.53	1535.0	1662.8	139.47	686.0	686.0	7.02	684.0	684.0	6.71
410	514	576.0	722.9	12.06	1143.0	1198.6	122.37	530.0	530.0	3.11	529.0	529.0	2.92
51	253	302.0	356.2	19.37	568.0	612.1	124.51	268.0	268.0	5.93	266.0	266.0	5.14
52	302	356.0	420.9	17.88	831.0	889.9	175.17	328.0	328.0	8.61	328.0	328.0	8.61
53	226	265.0	308.4	17.26	498.0	537.8	120.35	232.0	232.0	2.65	233.0	233.0	3.1
54	242	307.0	335.0	26.86	553.0	577.6	128.51	252.0	252.0	4.13	251.0	251.0	3.72
55	211	257.0	307.9	21.8	411.0	431.3	94.79	217.0	217.0	2.84	219.0	219.0	3.79
56	213	263.0	317.5	23.47	472.0	534.9	121.6	229.0	229.0	7.51	223.0	223.0	4.69
57	293	345.0	422.9	17.75	643.0	704.9	119.45	309.0	309.0	5.46	310.0	310.0	5.8
58	288	359.0	390.6	24.65	707.0	729.2	145.49	296.0	296.0	2.78	297.0	297.0	3.12
59	279	372.0	414.8	33.33	719.0	739.6	157.71	289.0	289.0	3.58	284.0	284.0	1.79
510	265	317.0	390.6	19.62	621.0	656.5	134.34	279.0	279.0	5.28	277.0	277.0	4.53
61	138	171.0	235.4	23.91	755.0	830.7	447.1	146.0	146.0	5.8	146.0	146.0	5.8
62	146	188.0	244.2	28.77	1092.0	1155.8	647.95	155.0	155.0	6.16	154.0	154.0	5.48
63	145	195.0	293.4	34.48	1091.0	1132.9	652.41	150.0	150.0	3.45	149.0	149.0	2.76
64	131	166.0	242.6	26.72	623.0	697.7	375.57	132.0	132.0	0.76	134.0	134.0	2.29
65	161	209.0	244.1	29.81	1000.0	1123.1	521.12	171.0	171.0	6.21	176.0	176.0	9.32
a1	253	286.0	308.1	13.04	1320.0	1343.3	421.74	267.0	267.0	5.53	266.0	266.0	5.14
a2	252	290.0	335.6	15.08	1175.0	1210.1	366.27	271.0	271.0	7.54	270.0	270.0	7.14
a3	232	265.0	289.9	14.22	1067.0	1170.2	359.91	242.0	242.0	4.31	243.0	243.0	4.74
a4	234	274.0	326.3	17.09	1095.0	1126.9	367.95	247.0	247.0	5.56	247.0	247.0	5.56
a5	236	276.0	319.3	16.95	1100.0	1165.1	366.1	249.0	249.0	5.51	246.0	246.0	4.24
b1	69	79.0	103.1	14.49	1341.0	1413.9	1843.48	71.0	71.0	2.9	71.0	71.0	2.9
b2	76	88.0	110.2	15.79	1364.0	1402.3	1694.74	78.0	78.0	2.63	78.0	78.0	2.63
b3	80	87.0	106.9	8.75	1670.0	1830.4	1987.5	82.0	82.0	2.5	82.0	82.0	2.5
b4	79	88.0	108.2	11.39	88.0	1461.8	11.39	83.0	83.0	5.06	82.0	82.0	3.8
b5	72	80.0	118.6	11.11	1404.0	1467.7	1850.0	74.0	74.0	2.78	74.0	74.0	2.78
c1	227	291.0	320.0	28.19	1508.0	1559.6	564.32	244.0	245.0	7.49	244.0	244.0	7.49
c2	219	271.0	287.0	23.74	1716.0	1770.6	683.56	239.0	239.0	9.13	238.0	238.0	8.68
c3	243	280.0	334.0	15.23	268.0	1880.5	10.29	259.0	259.0	6.58	257.0	257.0	5.76
c4	219	243.0	276.6	10.96	1657.0	1737.7	656.62	232.0	232.0	5.94	232.0	232.0	5.94
c5	215	268.0	287.8	24.65	1537.0	1649.7	614.88	230.0	230.0	6.98	229.0	229.0	6.51
d1	60	81.0	102.5	35.0	1979.0	2046.9	3198.33	65.0	65.0	8.33	64.0	64.0	6.67
d2	66	77.0	106.1	16.67	2201.0	2328.6	3234.85	69.0	69.0	4.55	69.0	69.0	4.55
d3	72	92.0	110.7	27.78	2413.0	2523.6	3251.39	76.0	76.0	5.56	76.0	76.0	5.56
d4	62	68.0	91.7	9.68	1929.0	2091.9	3011.29	63.0	63.0	1.61	63.0	63.0	1.61
d5	61	77.0	97.7	26.23	1979.0	2086.6	3144.26	65.0	65.0	6.56	64.0	64.0	4.92
		305.56	364.08	20.45	1123.22	1254.5	728.24	266.27	266.29	4.9	**265.33**	265.33	4.59

Table 14: SCP - WOA - 40 ACTIONS

Inst.	Opt.	BCL			MIR			BQSA1		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
41	429	542.0	583.7	26.34	683.0	713.4	59.21	441.0	441.0	2.8
42	512	756.0	809.9	47.66	1114.0	1163.8	117.58	548.0	548.0	7.03
43	516	739.0	846.9	43.22	1230.0	1264.7	138.37	541.0	541.0	4.84
44	494	596.0	739.8	20.65	954.0	1032.5	93.12	520.0	520.0	5.26
45	512	755.0	821.0	47.46	1121.0	1192.6	118.95	540.0	540.0	5.47
46	560	815.0	913.0	45.54	1391.0	1464.0	148.39	586.0	586.0	4.64
47	430	597.0	652.2	38.84	854.0	912.2	98.6	445.0	445.0	3.49
48	492	757.0	844.3	53.86	1148.0	1208.4	133.33	510.0	510.0	3.66
49	641	922.0	1031.1	43.84	1586.0	1678.7	147.43	689.0	689.0	7.49
410	514	696.0	787.2	35.41	1090.0	1153.4	112.06	522.0	525.0	1.56
51	253	378.0	398.4	49.41	582.0	607.0	130.04	265.0	266.0	4.74
52	302	502.0	542.2	66.23	804.0	879.0	166.23	328.0	328.0	8.61
53	226	320.0	363.3	41.59	506.0	547.0	123.89	234.0	234.0	3.54
54	242	318.0	366.5	31.4	540.0	566.6	123.14	252.0	252.0	4.13
55	211	305.0	327.7	44.55	397.0	417.5	88.15	217.0	217.0	2.84
56	213	358.0	379.3	68.08	531.0	540.8	149.3	224.0	224.0	5.16
57	293	387.0	475.7	32.08	642.0	703.8	119.11	310.0	310.0	5.8
58	288	422.0	468.7	46.53	673.0	732.6	133.68	297.0	297.0	3.12
59	279	430.0	495.5	54.12	698.0	728.8	150.18	281.0	281.0	0.72
510	265	429.0	455.2	61.89	594.0	655.2	124.15	277.0	277.0	4.53
61	138	285.0	356.5	106.52	752.0	818.9	444.93	147.0	147.0	6.52
62	146	413.0	509.5	182.88	1100.0	1175.9	653.42	155.0	155.0	6.16
63	145	337.0	450.9	132.41	1030.0	1099.7	610.34	150.0	150.0	3.45
64	131	286.0	327.3	118.32	655.0	704.3	400.0	135.0	135.0	3.05
65	161	357.0	429.1	121.74	1050.0	1124.6	552.17	174.0	176.5	8.07
a1	253	479.0	577.4	89.33	1243.0	1323.1	391.3	267.0	267.0	5.53
a2	252	452.0	613.1	79.37	1150.0	1211.2	356.35	271.0	271.0	7.54
a3	232	436.0	526.0	87.93	1117.0	1174.2	381.47	247.0	247.0	6.47
a4	234	469.0	558.6	100.43	1080.0	1136.9	361.54	248.0	248.0	5.98
a5	236	447.0	576.1	89.41	1139.0	1168.0	382.63	248.0	248.0	5.08
b1	69	380.0	509.0	450.72	1353.0	1407.2	1860.87	72.0	72.0	4.35
b2	76	374.0	508.2	392.11	1265.0	1372.7	1564.47	79.0	79.0	3.95
b3	80	468.0	574.8	485.0	1753.0	1808.5	2091.25	82.0	82.0	2.5
b4	79	372.0	589.4	370.89	1536.0	1616.1	1844.3	83.0	83.0	5.06
b5	72	376.0	440.5	422.22	1372.0	1441.0	1805.56	74.0	74.0	2.78
c1	227	523.0	671.9	130.4	1488.0	1581.9	555.51	248.0	248.0	9.25
c2	219	507.0	629.8	131.51	1654.0	1741.8	655.25	236.0	236.0	7.76
c3	243	629.0	759.5	158.85	2059.0	2123.0	747.33	259.0	259.0	6.58
c4	219	570.0	716.0	160.27	1645.0	1721.1	651.14	234.0	234.0	6.85
c5	215	496.0	636.9	130.7	1619.0	1684.6	653.02	228.0	229.5	6.05
d1	60	419.0	620.8	598.33	1950.0	2057.5	3150.0	65.0	65.5	8.33
d2	66	480.0	700.6	627.27	2264.0	2314.1	3330.3	69.0	69.0	4.55
d3	72	548.0	735.3	661.11	2445.0	2526.3	3295.83	77.0	77.0	6.94
d4	62	476.0	720.4	667.74	2025.0	2079.9	3166.13	63.0	63.0	1.61
d5	61	461.0	749.8	655.74	1930.0	2055.9	3063.93	64.0	64.0	4.92
		490.31	595.31	178.89	1195.83	1258.45	787.64	**266.71**	266.9	5.08

Table 16: SCP - GWO - 40 ACTIONS

		BCL			MIR			BQSA1		
Inst.	Opt.	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
41	429	432.0	433.5	0.7	431.0	434.4	0.47	439.0	439.0	2.33
42	512	533.0	539.1	4.1	543.0	547.8	6.05	543.0	543.0	6.05
43	516	527.0	532.5	2.13	541.0	546.3	4.84	534.0	534.0	3.49
44	494	507.0	514.3	2.63	513.0	520.5	3.85	523.0	523.0	5.87
45	512	523.0	528.2	2.15	540.0	549.6	5.47	547.0	547.0	6.84
46	560	570.0	579.1	1.79	579.0	583.2	3.39	584.0	584.0	4.29
47	430	434.0	437.8	0.93	442.0	445.7	2.79	448.0	448.0	4.19
48	492	499.0	506.3	1.42	509.0	512.6	3.46	510.0	510.5	3.66
49	641	656.0	671.4	2.34	685.0	690.3	6.86	694.0	694.0	8.27
410	514	520.0	525.7	1.17	528.0	531.2	2.72	530.0	530.0	3.11
51	253	260.0	265.8	2.77	264.0	266.5	4.35	269.0	269.0	6.32
52	302	322.0	328.3	6.62	326.0	333.7	7.95	331.0	331.0	9.6
53	226	230.0	233.3	1.77	232.0	234.2	2.65	231.0	232.5	2.21
54	242	247.0	249.8	2.07	250.0	253.1	3.31	252.0	252.0	4.13
55	211	212.0	213.8	0.47	216.0	217.9	2.37	219.0	219.0	3.79
56	213	216.0	223.8	1.41	222.0	228.2	4.23	230.0	230.0	7.98
57	293	299.0	306.8	2.05	309.0	311.8	5.46	312.0	312.0	6.48
58	288	290.0	296.2	0.69	297.0	300.7	3.12	300.0	300.0	4.17
59	279	282.0	285.0	1.08	285.0	293.0	2.15	290.0	290.0	3.94
510	265	269.0	275.0	1.51	277.0	280.7	4.53	277.0	277.0	4.53
61	138	140.0	145.2	1.45	144.0	148.1	4.35	147.0	147.0	6.52
62	146	147.0	152.3	0.68	155.0	158.9	6.16	157.0	157.0	7.53
63	145	147.0	149.8	1.38	151.0	151.5	4.14	151.0	151.0	4.14
64	131	131.0	134.3	0.0	134.0	135.3	2.29	132.0	132.0	0.76
65	161	167.0	172.3	3.73	175.0	183.7	8.7	179.0	180.0	11.18
a1	253	262.0	263.2	3.56	271.0	277.6	7.11	269.0	269.0	6.32
a2	252	263.0	268.1	4.37	275.0	279.2	9.13	273.0	273.0	8.33
a3	232	241.0	245.3	3.88	250.0	256.1	7.76	248.0	248.0	6.9
a4	234	244.0	247.4	4.27	250.0	257.8	6.84	248.0	248.0	5.98
a5	236	244.0	246.5	3.39	255.0	259.0	8.05	249.0	249.0	5.51
b1	69	70.0	71.1	1.45	75.0	81.5	8.7	73.0	73.0	5.8
b2	76	76.0	78.3	0.0	86.0	91.3	13.16	80.0	80.0	5.26
b3	80	81.0	82.2	1.25	89.0	98.1	11.25	84.0	84.0	5.0
b4	79	82.0	82.9	3.8	95.0	100.0	20.25	85.0	85.0	7.59
b5	72	73.0	73.5	1.39	81.0	90.5	12.5	75.0	75.0	4.17
c1	227	239.0	248.1	5.29	263.0	272.7	15.86	252.0	252.5	11.01
c2	219	233.0	238.1	6.39	260.0	265.0	18.72	239.0	239.0	9.13
c3	243	252.0	257.3	3.7	279.0	289.1	14.81	264.0	264.0	8.64
c4	219	233.0	235.7	6.39	250.0	257.9	14.16	238.0	238.0	8.68
c5	215	226.0	229.4	5.12	248.0	256.3	15.35	234.0	234.0	8.84
d1	60	62.0	63.5	3.33	83.0	98.2	38.33	66.0	66.0	10.0
d2	66	66.0	68.3	0.0	97.0	113.7	46.97	71.0	71.0	7.58
d3	72	75.0	76.4	4.17	108.0	121.6	50.0	80.0	80.0	11.11
d4	62	62.0	63.5	0.0	90.0	101.9	45.16	64.0	65.0	3.23
d5	61	61.0	64.0	0.0	97.0	106.4	59.02	66.0	66.0	8.2
		260.11	264.5	2.42	272.22	278.51	11.75	268.6	268.7	6.19

Table 18: SCP - SCA - 40 ACTIONS

Inst.	Opt.	BCL			MIR			BQSA1		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
41	429	526.0	577.8	22.61	689.0	707.2	60.61	439.0	440.0	2.33
42	512	600.0	720.5	17.19	1060.0	1165.8	107.03	551.0	551.0	7.62
43	516	589.0	741.6	14.15	1185.0	1269.0	129.65	546.0	546.0	5.81
44	494	580.0	709.2	17.41	986.0	1020.8	99.6	530.0	530.0	7.29
45	512	700.0	810.1	36.72	1126.0	1184.3	119.92	546.0	546.0	6.64
46	560	692.0	793.2	23.57	1421.0	1475.5	153.75	585.0	585.0	4.46
47	430	498.0	606.0	15.81	886.0	920.3	106.05	448.0	448.0	4.19
48	492	577.0	719.3	17.28	1119.0	1226.7	127.44	515.0	515.0	4.67
49	641	779.0	918.0	21.53	1535.0	1662.8	139.47	691.0	691.0	7.8
410	514	576.0	722.9	12.06	1143.0	1198.6	122.37	529.0	529.0	2.92
51	253	302.0	356.2	19.37	568.0	612.1	124.51	269.0	269.0	6.32
52	302	356.0	420.9	17.88	831.0	889.9	175.17	331.0	331.0	9.6
53	226	265.0	308.4	17.26	498.0	537.8	120.35	234.0	234.0	3.54
54	242	307.0	335.0	26.86	553.0	577.6	128.51	252.0	252.0	4.13
55	211	257.0	307.9	21.8	411.0	431.3	94.79	219.0	219.0	3.79
56	213	263.0	317.5	23.47	472.0	534.9	121.6	232.0	232.0	8.92
57	293	345.0	422.9	17.75	643.0	704.9	119.45	315.0	315.0	7.51
58	288	359.0	390.6	24.65	707.0	729.2	145.49	300.0	300.0	4.17
59	279	372.0	414.8	33.33	719.0	739.6	157.71	290.0	290.0	3.94
510	265	317.0	390.6	19.62	621.0	656.5	134.34	280.0	280.0	5.66
61	138	171.0	235.4	23.91	755.0	830.7	447.1	144.0	144.0	4.35
62	146	188.0	244.2	28.77	1092.0	1155.8	647.95	158.0	158.0	8.22
63	145	195.0	293.4	34.48	1091.0	1132.9	652.41	149.0	150.0	2.76
64	131	166.0	242.6	26.72	623.0	697.7	375.57	135.0	135.0	3.05
65	161	209.0	244.1	29.81	1000.0	1123.1	521.12	183.0	183.0	13.66
a1	253	286.0	308.1	13.04	1320.0	1343.3	421.74	265.0	265.0	4.74
a2	252	290.0	335.6	15.08	1175.0	1210.1	366.27	273.0	273.0	8.33
a3	232	265.0	289.9	14.22	1067.0	1170.2	359.91	245.0	245.0	5.6
a4	234	274.0	326.3	17.09	1095.0	1126.9	367.95	254.0	254.0	8.55
a5	236	276.0	319.3	16.95	1100.0	1165.1	366.1	252.0	252.0	6.78
b1	69	79.0	103.1	14.49	1341.0	1413.9	1843.48	72.0	72.0	4.35
b2	76	88.0	110.2	15.79	1364.0	1402.3	1694.74	80.0	80.0	5.26
b3	80	87.0	106.9	8.75	1670.0	1830.4	1987.5	82.0	82.0	2.5
b4	79	88.0	108.2	11.39	88.0	1461.8	11.39	84.0	84.0	6.33
b5	72	80.0	118.6	11.11	1404.0	1467.7	1850.0	74.0	74.0	2.78
c1	227	291.0	320.0	28.19	1508.0	1559.6	564.32	245.0	245.0	7.93
c2	219	271.0	287.0	23.74	1716.0	1770.6	683.56	239.0	239.5	9.13
c3	243	280.0	334.0	15.23	268.0	1880.5	10.29	261.0	261.0	7.41
c4	219	243.0	276.6	10.96	1657.0	1737.7	656.62	236.0	236.0	7.76
c5	215	268.0	287.8	24.65	1537.0	1649.7	614.88	232.0	232.0	7.91
d1	60	81.0	102.5	35.0	1979.0	2046.9	3198.33	64.0	64.0	6.67
d2	66	77.0	106.1	16.67	2201.0	2328.6	3234.85	69.0	69.0	4.55
d3	72	92.0	110.7	27.78	2413.0	2523.6	3251.39	78.0	78.0	8.33
d4	62	68.0	91.7	9.68	1929.0	2091.9	3011.29	64.0	64.0	3.23
d5	61	77.0	97.7	26.23	1979.0	2086.6	3144.26	66.0	66.0	8.2
		305.56	364.08	20.45	1123.22	1254.5	728.24	**269.02**	269.08	5.99

Table 19: 0-1KP - WOA - Q-Learning

Inst.	Opt.	QL1 Best	QL1 Avg	QL1 RPD	QL2 Best	QL2 Avg	QL2 RPD	QL3 Best	QL3 Avg	QL3 RPD	QL4 Best	QL4 Avg	QL4 RPD	QL5 Best	QL5 Avg	QL5 RPD
KP1	295	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0
KP2	1024	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0
KP3	35	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0
KP4	23	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0
KP5	481.0694	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0
KP6	52	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0
KP7	107	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0
KP8	9767	9762.0	9765.16	0.05	9761.0	9764.84	0.06	9761.0	9764.68	0.06	9762.0	9765.1	0.05	9761.0	9765.52	0.06
KP9	130	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0
KP10	1025	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0
KP1 100	9147	5412.0	6174.74	40.83	5416.0	7031.06	40.79	5059.0	6574.48	44.69	5012.0	6814.52	45.21	5063.0	6679.1	44.65
KP1 200	11238	5402.0	6910.97	51.93	5491.0	7580.1	51.14	5861.0	8612.13	47.85	4661.0	8260.16	58.52	5790.0	8199.1	48.48
KP1 500	28857	8651.0	9749.9	70.02	8353.0	12546.35	71.05	7727.0	11999.9	73.22	7886.0	13013.03	72.67	8224.0	11591.06	71.5
KP3 100	1514	1277.0	1335.58	15.65	1258.0	1345.58	16.91	1249.0	1337.06	17.5	1229.0	1347.1	18.82	1245.0	1326.97	17.77
KP3 200	1634	1260.0	1341.81	22.89	1283.0	1411.58	21.48	1268.0	1417.9	22.4	1246.0	1420.9	23.75	1262.0	1414.68	22.77
KP3 500	4566	2956.0	3128.55	35.26	2989.0	3564.68	34.54	2958.0	3581.7	35.22	3014.0	3595.7	33.99	2937.0	3436.0	35.68
KP3 100	2397	1896.0	2070.9	20.9	1892.0	2215.68	21.07	1869.0	2234.23	22.03	1895.0	2287.19	20.94	1975.0	2265.52	17.61
KP3 200	2697	1993.0	2101.61	26.1	1897.0	2328.68	29.66	1794.0	2303.61	33.48	1985.0	2446.94	26.4	1896.0	2401.74	29.7
KP3 500	7117	4017.0	4245.16	43.56	3916.0	5201.58	44.98	3815.0	4607.45	46.4	3916.0	4830.52	44.98	3917.0	4910.83	44.96
		2410.42	2631.39	17.22	2390.95	2955.91	17.46	2343.85	2926.59	18.04	2304.11	2997.54	18.18	2381.16	2903.29	17.54

Table 20: 0-1KP - WOA - SARSA

Inst.	Opt.	SA1 Best	SA1 Avg	SA1 RPD	SA2 Best	SA2 Avg	SA2 RPD	SA3 Best	SA3 Avg	SA3 RPD	SA4 Best	SA4 Avg	SA4 RPD	SA5 Best	SA5 Avg	SA5 RPD
KP1	295	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0
KP2	1024	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0
KP3	35	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0
KP4	23	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0
KP5	481.0694	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0
KP6	52	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0
KP7	107	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0
KP8	9767	9762.0	9765.23	0.05	9761.0	9764.9	0.06	9761.0	9765.55	0.06	9762.0	9765.32	0.05	9763.0	9765.79	0.04
KP9	130	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0
KP10	1025	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0
KP1 100	9147	5142.0	6121.55	43.78	5177.0	5977.94	43.4	5092.0	5864.55	44.33	5205.0	5990.81	43.1	5478.0	5981.74	40.11
KP1 200	11238	5220.0	6413.52	53.55	5559.0	6241.13	50.53	5208.0	6189.61	53.66	5270.0	6080.16	53.11	5465.0	6293.58	51.37
KP1 500	28857	7896.0	9086.35	72.64	7297.0	8718.61	74.71	6878.0	8604.9	76.17	7715.0	8899.55	73.26	7132.0	8442.39	75.29
KP2 100	1514	1240.0	1326.35	18.1	1247.0	1304.35	17.64	1234.0	1302.35	18.49	1247.0	1298.26	17.64	1237.0	1295.26	18.3
KP2 200	1634	1259.0	1346.87	22.95	1265.0	1314.19	22.58	1266.0	1325.52	22.52	1239.0	1309.68	24.17	1270.0	1313.55	22.28
KP2 500	4566	3011.0	3134.39	34.06	2974.0	3069.19	34.87	2947.0	3036.27	35.46	2953.0	3053.46	35.33	2965.0	3072.32	35.06
KP3 100	2397	1879.0	2034.81	21.61	1887.0	2037.26	21.28	1895.0	2002.42	20.94	1797.0	2018.6	25.03	1888.0	2005.71	21.23
KP3 200	2697	1995.0	2106.74	26.03	1896.0	2014.1	29.7	1895.0	2058.84	29.74	1796.0	2044.52	33.41	1897.0	2050.06	29.66
KP3 500	7117	4017.0	4244.81	43.56	4017.0	4176.97	43.56	4013.0	4112.52	43.61	4015.0	4174.14	43.59	4015.0	4174.35	43.59
		2347.0	2565.93	17.7	2329.06	2515.3	17.81	2282.16	2496.56	18.16	2324.79	2516.14	18.35	2330.64	2503.52	17.73

Table 21: 0-1KP - GWO - Q-Learning

Inst.	Opt.	QL1 Best	QL1 Avg	QL1 RPD	QL2 Best	QL2 Avg	QL2 RPD	QL3 Best	QL3 Avg	QL3 RPD	QL4 Best	QL4 Avg	QL4 RPD	QL5 Best	QL5 Avg	QL5 RPD
KP1	295	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0
KP2	1024	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0
KP3	35	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0
KP4	23	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0
KP5	481.0694	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0
KP6	52	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0
KP7	107	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0
KP8	9767	9760.0	9763.84	0.07	9762.0	9764.16	0.05	9760.0	9763.55	0.07	9759.0	9762.84	0.08	9759.0	9763.26	0.08
KP9	130	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0
KP10	1025	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0
KP1 100	9147	6347.0	6947.19	30.61	5824.0	6547.26	36.33	5733.0	6508.65	37.32	5814.0	6622.1	36.44	5829.0	6551.06	36.27
KP1 200	11238	6480.0	7254.06	42.34	6227.0	6961.65	44.59	6024.0	6949.94	46.4	6283.0	6929.77	44.09	6061.0	6867.58	46.07
KP1 500	28857	8800.0	10045.16	69.5	8358.0	9773.97	71.04	8905.0	10083.84	69.14	8786.0	9920.03	69.55	8646.0	9807.03	70.04
KP2 100	1514	1314.0	1369.84	13.21	1296.0	1353.71	14.4	1288.0	1346.58	14.93	1281.0	1346.48	15.39	1293.0	1350.65	14.6
KP2 200	1634	1349.0	1402.94	17.44	1301.0	1377.61	20.38	1290.0	1367.19	21.05	1314.0	1360.23	19.58	1301.0	1374.16	20.38
KP2 500	4566	3136.0	3217.06	31.32	3042.0	3124.84	33.38	3008.0	3160.48	34.12	3025.0	3144.13	33.75	3078.0	3136.9	32.59
KP3 100	2397	1996.0	2124.94	16.73	1981.0	2080.45	17.36	1990.0	2050.71	16.98	1990.0	2057.87	16.98	1995.0	2079.13	16.77
KP3 200	2697	2087.0	2158.1	22.62	1987.0	2129.45	26.33	1995.0	2112.87	26.03	1997.0	2116.65	25.95	1996.0	2135.35	25.99
KP3 500	7117	4213.0	4335.16	40.8	4113.0	4306.1	42.21	4117.0	4315.35	42.15	4117.0	4344.68	42.15	4116.0	4293.26	42.17
		2560.74	2725.81	14.98	2477.0	2662.7	16.11	2488.53	2675.33	16.22	2502.0	2672.47	16.0	2486.64	2659.5	16.05

Table 22: 0-1KP - GWO - SARSA

Inst.	Opt.	SA1 Best	SA1 Avg	SA1 RPD	SA2 Best	SA2 Avg	SA2 RPD	SA3 Best	SA3 Avg	SA3 RPD	SA4 Best	SA4 Avg	SA4 RPD	SA5 Best	SA5 Avg	SA5 RPD
KP1	295	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0
KP2	1024	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0
KP3	35	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0
KP4	23	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0
KP5	481.0694	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0
KP6	52	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0
KP7	107	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0
KP8	9767	9761.0	9764.39	0.06	9761.0	9764.32	0.06	9760.0	9764.97	0.07	9761.0	9764.52	0.06	9761.0	9763.87	0.06
KP9	130	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0
KP10	1025	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0
KP1 100	9147	5890.0	6816.55	35.61	6185.0	6885.0	32.38	6011.0	6702.81	34.28	6086.0	6737.68	33.46	6082.0	6645.81	33.51
KP1 200	11238	6597.0	7069.19	41.3	6348.0	7149.1	43.51	6593.0	7163.77	41.33	6464.0	7288.0	42.48	6349.0	7207.68	43.5
KP1 500	28857	9362.0	10158.1	67.56	9337.0	10113.26	67.64	9166.0	10135.55	68.24	8784.0	10215.55	69.56	8994.0	10071.23	68.83
KP2 100	1514	1299.0	1369.23	14.2	1309.0	1371.55	13.54	1311.0	1364.81	13.41	1313.0	1370.77	13.28	1317.0	1364.84	13.01
KP2 200	1634	1329.0	1383.65	18.67	1341.0	1387.97	17.93	1329.0	1387.55	18.67	1337.0	1390.58	18.18	1339.0	1383.16	18.05
KP2 500	4566	3126.0	3207.55	31.54	3121.0	3191.68	31.65	3124.0	3179.77	31.58	3111.0	3204.58	31.87	3140.0	3203.65	31.23
KP3 100	2397	1997.0	2102.29	16.69	1996.0	2096.1	16.73	1997.0	2095.81	16.69	1996.0	2085.03	16.73	1996.0	2100.45	16.73
KP3 200	2697	2089.0	2165.52	22.54	2092.0	2126.68	22.43	2080.0	2147.13	22.88	1996.0	2137.65	25.99	1997.0	2137.48	25.95
KP3 500	7117	4215.0	4370.58	40.78	4117.0	4360.39	42.15	4217.0	4341.71	40.75	4216.0	4350.97	40.76	4216.0	4376.23	40.76
		2570.37	2714.69	15.21	2567.32	2716.74	15.16	2566.32	2708.21	15.15	2538.74	2721.97	15.39	2545.42	2706.66	15.35

Table 23: 0-1KP - SCA - QL

Inst.	Opt.	QL1			QL2			QL3			QL4			QL5		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
KP1	295	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0
KP2	1024	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0
KP3	35	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0
KP4	23	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0
KP5	481.0694	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0
KP6	52	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0
KP7	107	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0
KP8	9767	9758.0	9762.06	0.09	9759.0	9763.06	0.08	9759.0	9762.87	0.08	9758.0	9762.19	0.09	9759.0	9762.87	0.08
KP9	130	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0
KP10	1025	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0
KP1 100	9147	5330.0	6174.55	41.73	5173.0	6138.61	43.45	5205.0	6652.0	43.1	4787.0	6307.84	47.67	5179.0	6529.35	43.38
KP1 200	11238	5585.0	6644.39	50.3	5598.0	6950.35	50.19	5573.0	7194.94	50.41	5794.0	7016.19	48.44	5370.0	6661.84	52.22
KP1 500	28857	8024.0	9218.26	72.19	7736.0	10809.55	73.19	7541.0	11591.32	73.87	7616.0	10568.84	73.61	7898.0	10635.29	72.63
KP2 100	1514	1260.0	1322.13	16.78	1249.0	1311.48	17.5	1230.0	1317.87	18.76	1244.0	1320.19	17.83	1255.0	1328.29	17.11
KP2 200	1634	1257.0	1335.35	23.07	1258.0	1334.58	23.01	1244.0	1357.94	23.87	1239.0	1344.29	24.17	1208.0	1333.32	26.07
KP2 500	4566	3006.0	3111.71	34.17	2987.0	3113.03	34.58	2954.0	3179.23	35.3	2984.0	3210.74	34.65	2987.0	3210.71	34.58
KP3 100	2397	1894.0	2027.9	20.98	1891.0	2149.97	21.11	1966.0	2120.55	17.98	1897.0	2135.29	20.86	1989.0	2116.58	17.02
KP3 200	2697	1994.0	2090.77	26.07	1896.0	2199.1	29.7	1990.0	2178.81	26.21	1962.0	2131.39	27.25	1797.0	2207.13	33.37
KP3 500	7117	4017.0	4200.16	43.56	3817.0	4646.52	46.37	3916.0	4486.52	44.98	3917.0	4484.48	44.96	3917.0	4482.23	44.96
		2384.06	2582.07	17.31	2344.0	2715.17	17.85	2344.74	2790.22	17.61	2335.27	2708.08	17.87	2343.74	2707.35	17.97

Table 24: 0-1KP - SCA - SARSA

Inst.	Opt.	SA1			SA2			SA3			SA4			SA5		
		Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD	Best	Avg	RPD
KP1	295	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0	295.0	295.0	0.0
KP2	1024	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0	1024.0	1024.0	0.0
KP3	35	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0	35.0	35.0	0.0
KP4	23	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0	23.0	23.0	0.0
KP5	481.0694	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0	481.07	481.07	0.0
KP6	52	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0	52.0	52.0	0.0
KP7	107	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0	107.0	107.0	0.0
KP8	9767	9759.0	9762.86	0.08	9758.0	9761.67	0.09	9759.0	9761.97	0.08	9756.0	9761.74	0.11	9757.0	9762.06	0.1
KP9	130	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0	130.0	130.0	0.0
KP10	1025	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0	1025.0	1025.0	0.0
KP1 100	9147	5565.0	6136.16	39.16	5225.0	6033.94	42.88	5282.0	6080.81	42.25	5178.0	5874.16	43.39	5313.0	6030.87	41.92
KP1 200	11238	5602.0	6322.77	50.15	5232.0	6239.94	53.44	5492.0	6288.52	51.13	5701.0	6677.0	49.27	5342.0	6281.13	52.46
KP1 500	28857	8428.0	9456.52	70.79	7478.0	8854.65	74.09	7158.0	8683.52	75.19	7557.0	9321.52	73.81	7455.0	9040.1	74.17
KP2 100	1514	1242.0	1316.16	17.97	1248.0	1302.87	17.57	1238.0	1315.13	18.23	1236.0	1298.32	18.36	1247.0	1316.84	17.64
KP2 200	1634	1258.0	1346.48	23.01	1259.0	1327.45	22.95	1251.0	1348.74	23.44	1252.0	1322.52	23.38	1239.0	1309.42	24.17
KP2 500	4566	2997.0	3120.45	34.36	2979.0	3106.1	34.76	2934.0	3082.77	35.74	2960.0	3094.77	35.17	2968.0	3065.84	35.0
KP3 100	2397	1896.0	2058.81	20.9	1893.0	2032.0	21.03	1896.0	1998.42	20.9	1896.0	2006.29	20.9	1897.0	2050.19	20.86
KP3 200	2697	1989.0	2078.61	26.25	1991.0	2041.71	26.18	1897.0	2102.23	29.66	1896.0	2058.77	29.7	1894.0	2076.84	29.77
KP3 500	7117	4015.0	4202.3	43.59	3917.0	4181.71	44.96	3917.0	4275.23	44.96	4016.0	4214.39	43.57	3917.0	4170.9	44.96
		2417.0	2577.54	17.17	2323.79	2529.16	17.79	2315.58	2532.07	17.98	2348.42	2568.5	17.77	2326.37	2540.86	17.95

Statical test of SCP

PONTIFICIA UNIVERSIDAD CATÓLICA DE VALPARAÍSO

Statistical test of Metheuristics WOA and 85 Actions solving SCP

Inst.	BCL	MIR	QL1	SA1
BCL	-	0.0	>0.05	>0.05
MIR	>0.05	-	>0.05	>0.05
QL1	0.0	0.0	-	>0.05
SA1	0.0	0.0	>0.05	-

Statistical test of Metheuristics GWO and 85 Actions solving SCP

Inst.	BCL	MIR	QL1	SA1
BCL	-	0.03	>0.05	>0.05
MIR	>0.05	-	>0.05	>0.05
QL1	>0.05	>0.05	-	>0.05
SA1	>0.05	0.02	>0.05	-

Statistical test of Metheuristics SCA and 85 Actions solving SCP

Inst.	BCL	MIR	QL1	SA1
BCL	-	0.0	>0.05	>0.05
MIR	>0.05	-	>0.05	>0.05
QL1	0.0	0.0	-	>0.05
SA1	0.0	0.0	>0.05	-

Statical test of SCP

Statistical test of Metheuristics WOA and 40 Actions solving SCP

Inst.	BCL	MIR	BQSA1
BCL	-	0.0	>0.05
MIR	>0.05	-	>0.05
BQSA1	0.0	0.0	-

Statistical test of Metheuristics GWO and 40 Actions solving SCP

Inst.	BCL	MIR	BQSA1
BCL	-	0.03	>0.05
MIR	>0.05	-	>0.05
BQSA1	>0.05	>0.05	-

Statistical test of Metheuristics SCA and 40 Actions solving SCP

Inst.	BCL	MIR	BQSA1
BCL	-	0.0	>0.05
MIR	>0.05	-	>0.05
BQSA1	0.0	0.0	-

Statical test of 0-1KP

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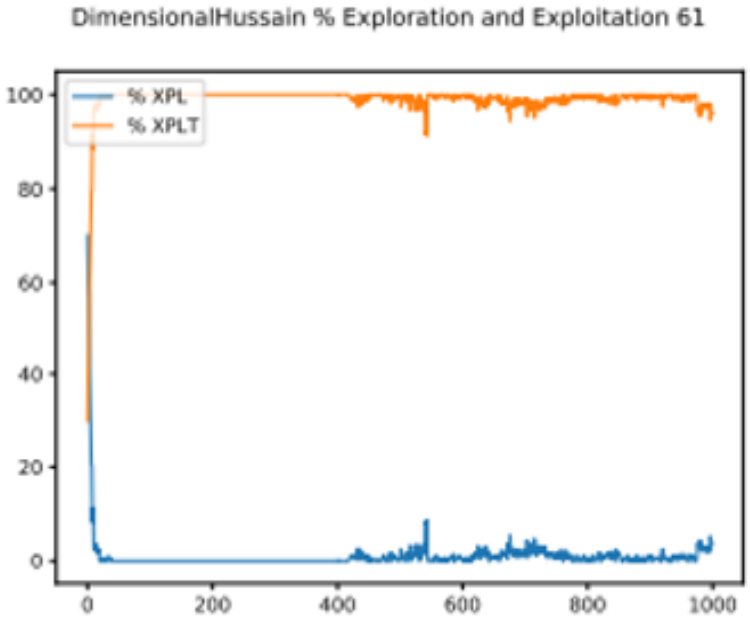
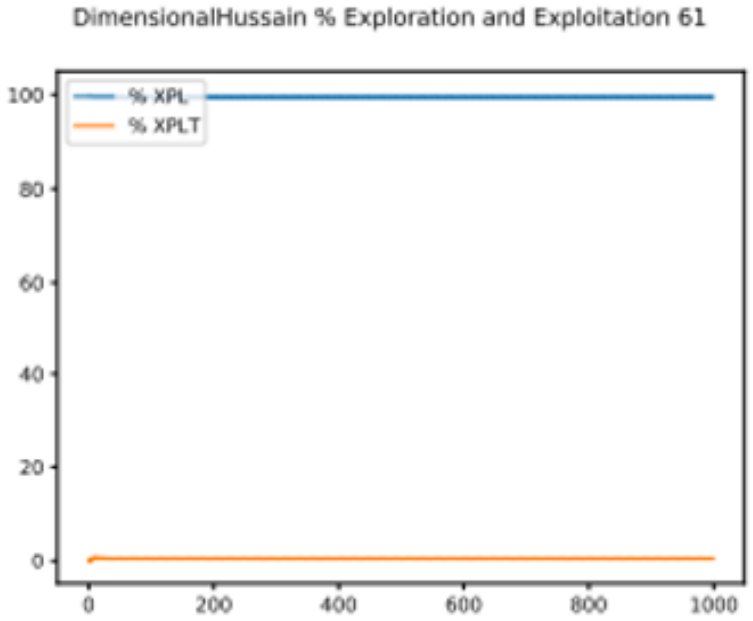
Statistical test of Metheuristics WOA solving 0-1KP

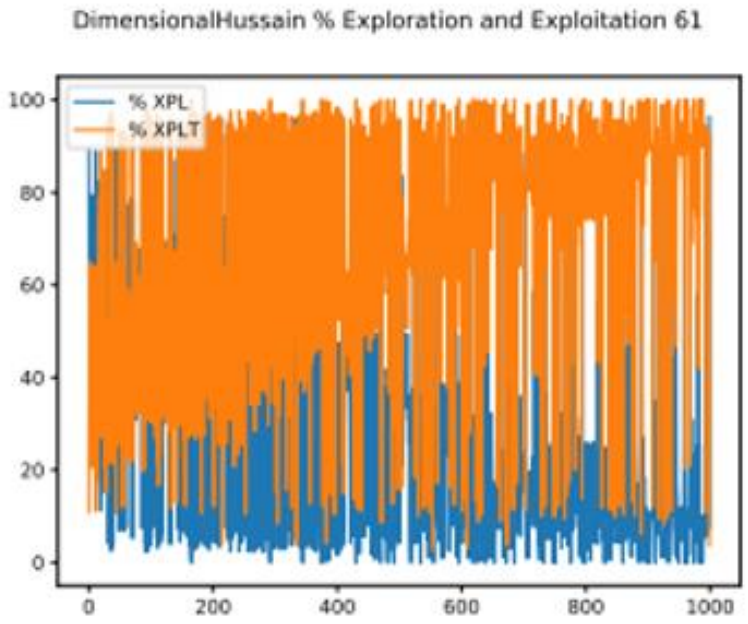
Inst.	QL1	QL2	QL3	QL4	QL5	SA1	SA2	SA3	SA4	SA5
QL1	-	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05
QL2	>0.05	-	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05
QL3	>0.05	>0.05	-	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05
QL4	>0.05	>0.05	>0.05	-	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05
QL5	>0.05	>0.05	>0.05	>0.05	-	>0.05	>0.05	>0.05	>0.05	>0.05
SA1	>0.05	>0.05	>0.05	>0.05	>0.05	-	>0.05	>0.05	>0.05	>0.05
SA2	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	-	>0.05	>0.05	>0.05
SA3	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	-	>0.05	>0.05
SA4	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	-	>0.05
SA5	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	>0.05	-

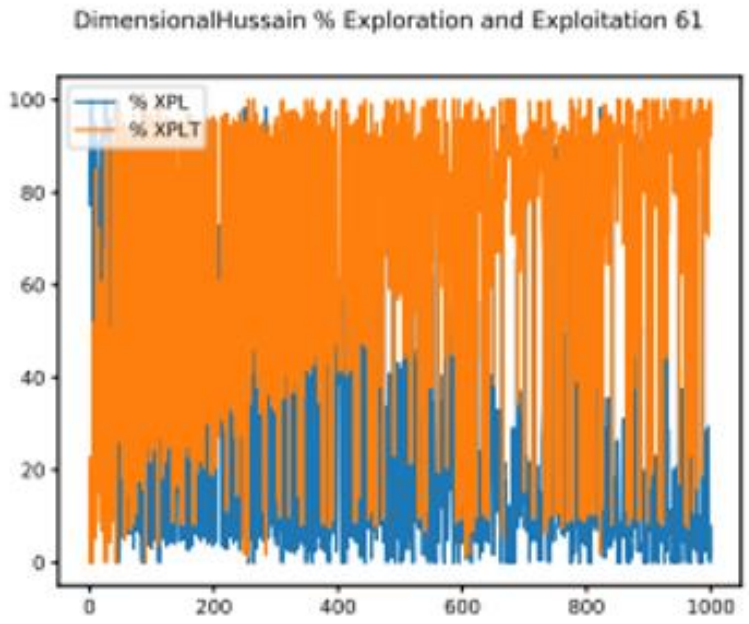
Exploration-Exploitation Graphics of SCP – WOA-BCL/WOA-MIR



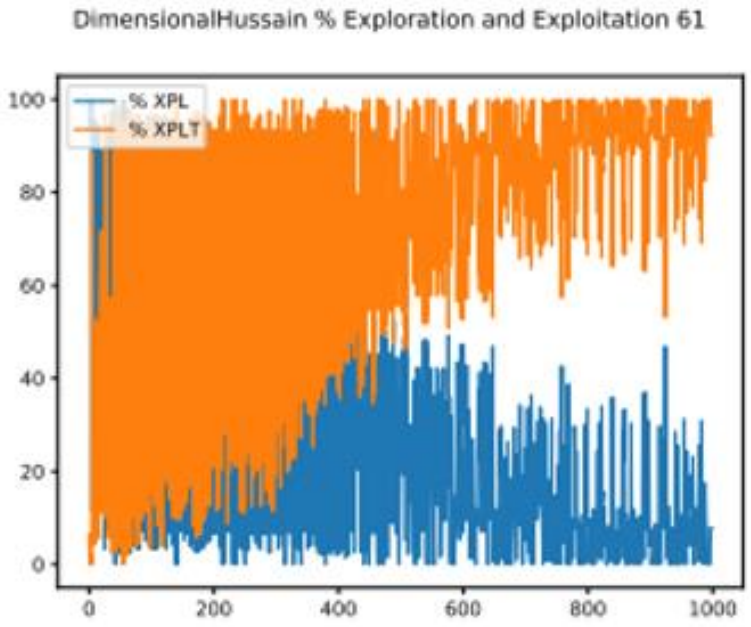


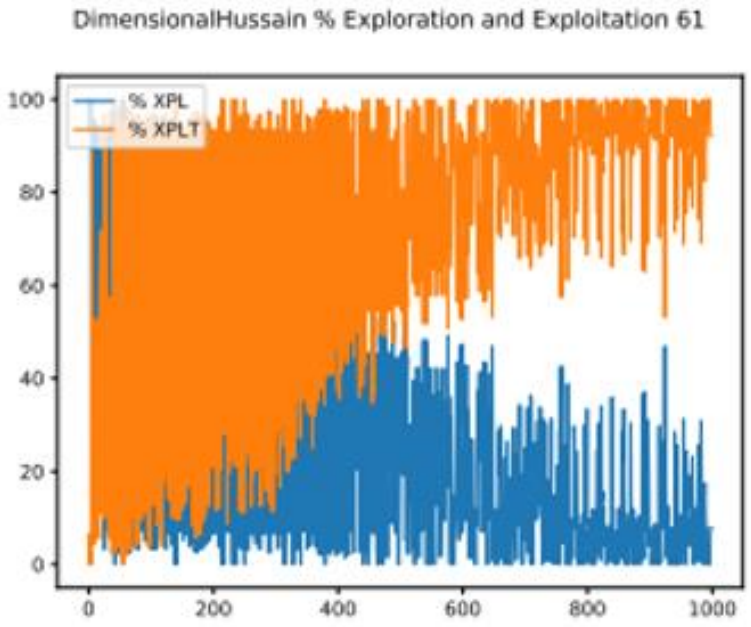
Exploration-Exploitation Graphics of SCP – WOA-QL/WOA-SARSA



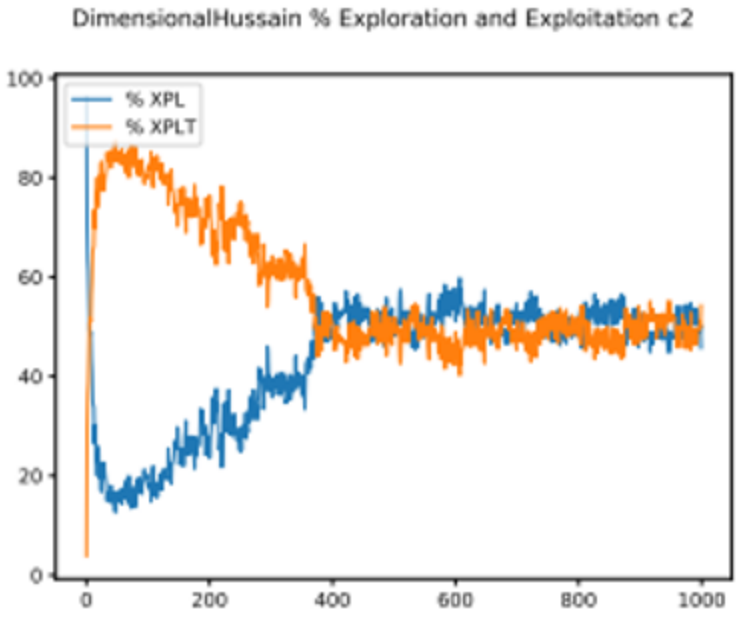


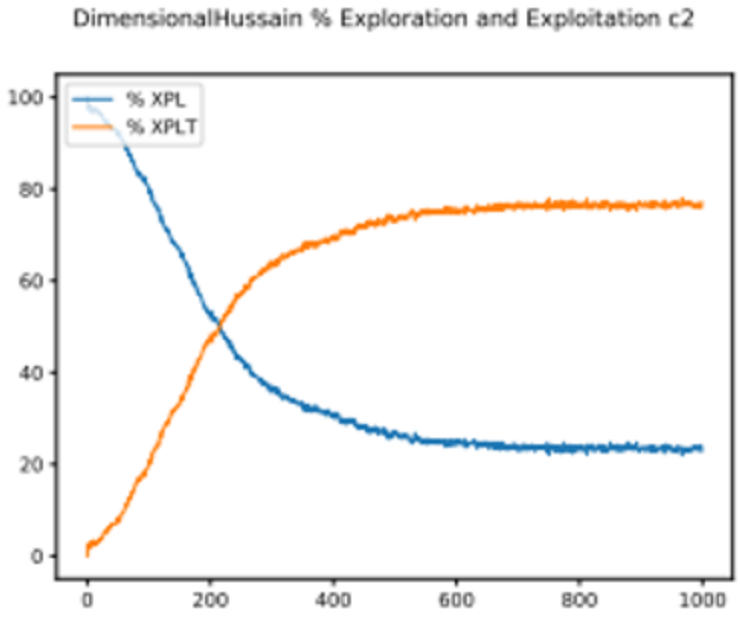
Exploration-Exploitation Graphics of SCP – WOA-BQSA



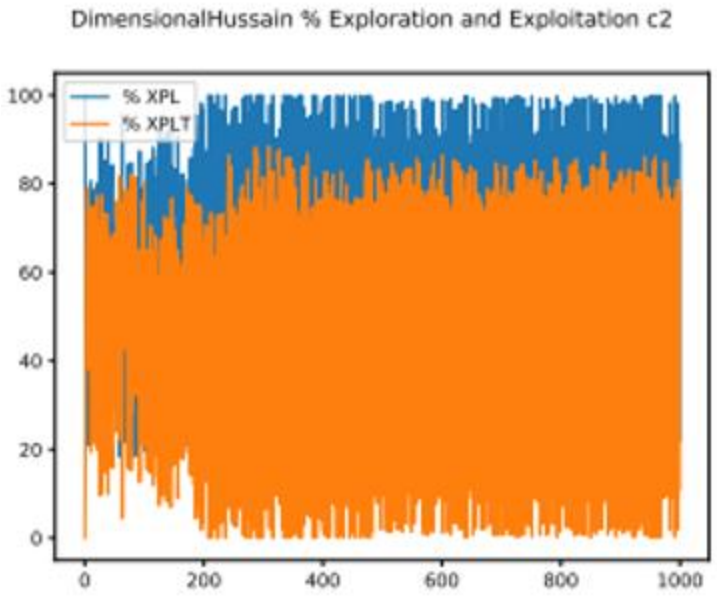


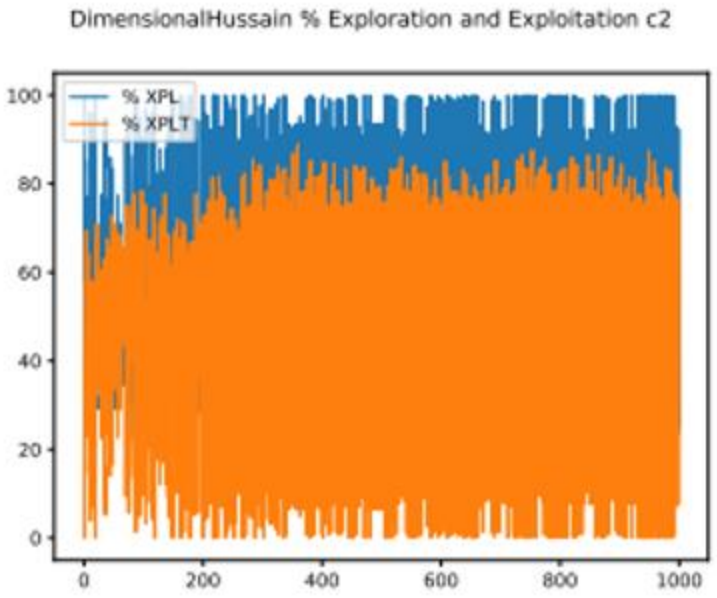
Exploration-Exploitation Graphics of SCP – GWO-BCL/GWO-MIR



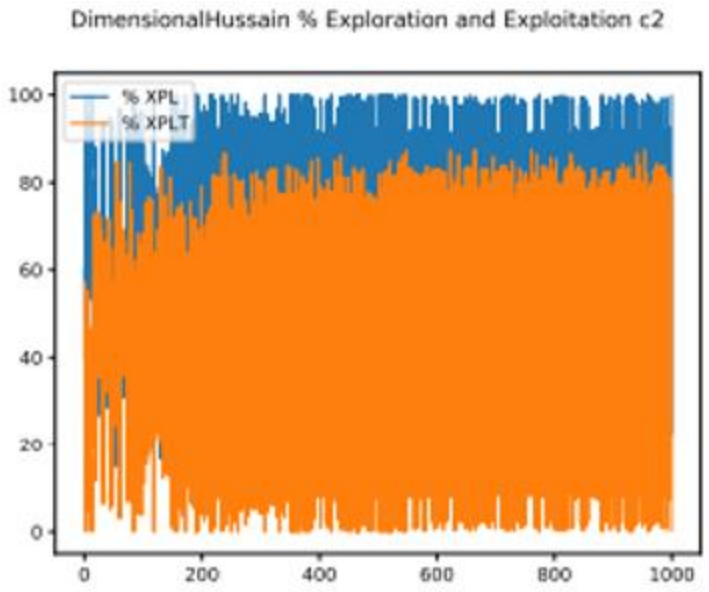


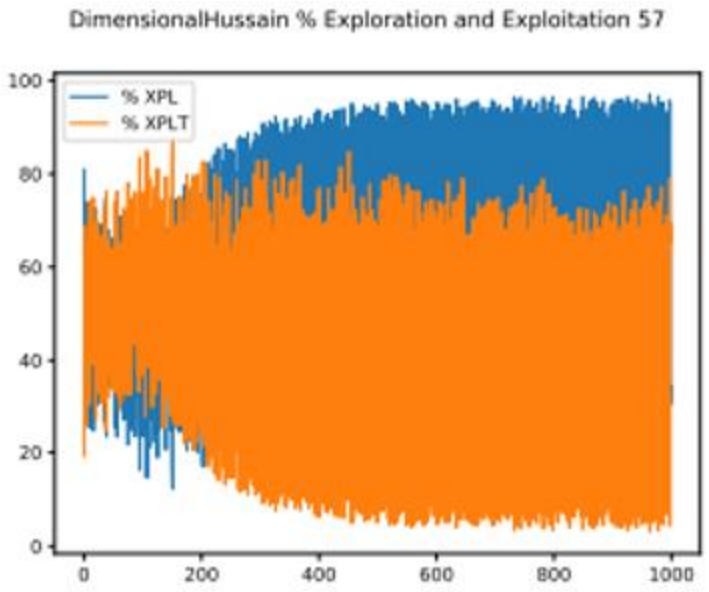
Exploration-Exploitation Graphics of SCP – GWO-QL/GWO-SARSA



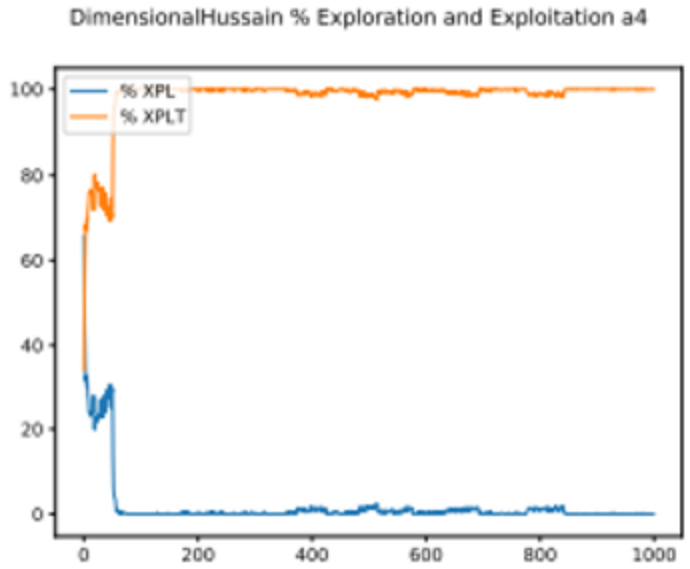


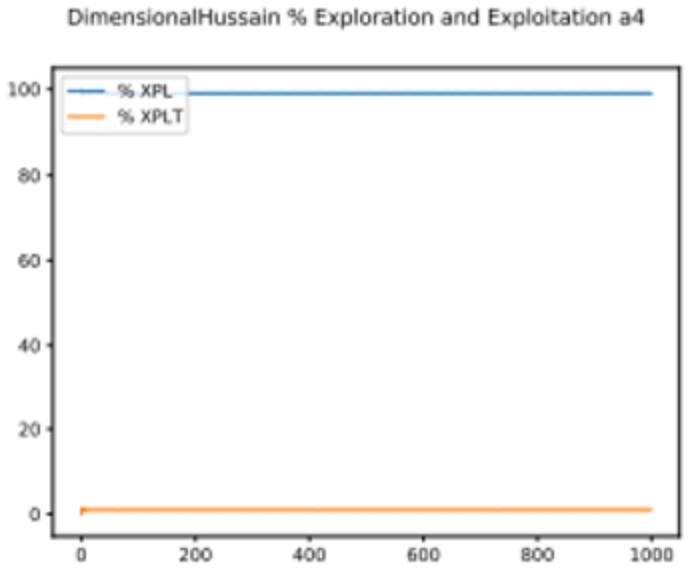
Exploration-Exploitation Graphics of SCP – GWO-BQSA



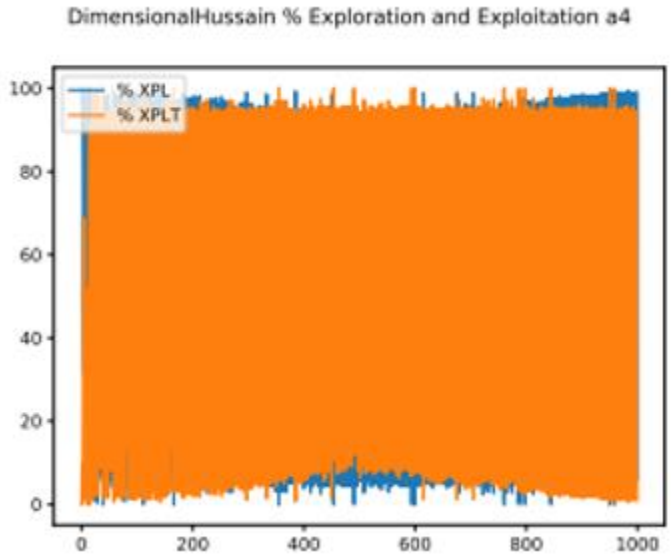


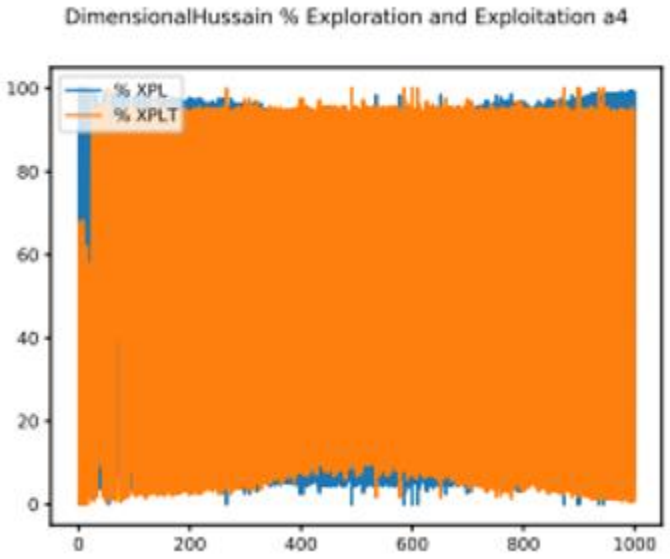
Exploration-Exploitation Graphics of SCP – SCA-BCL/SCA-MIR



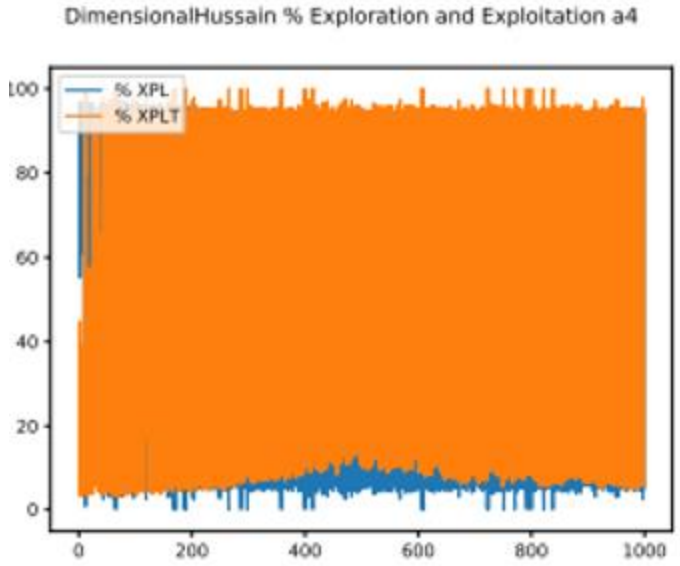


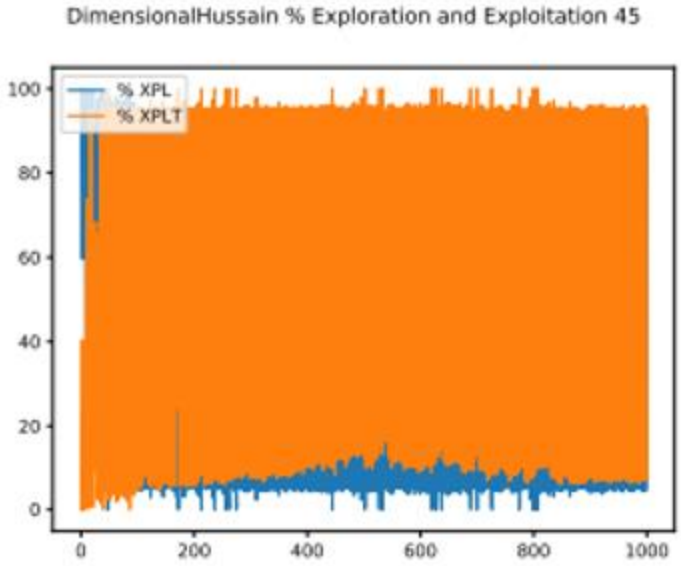
Exploration-Exploitation Graphics of SCP – SCA-QL/SCA-SARSA



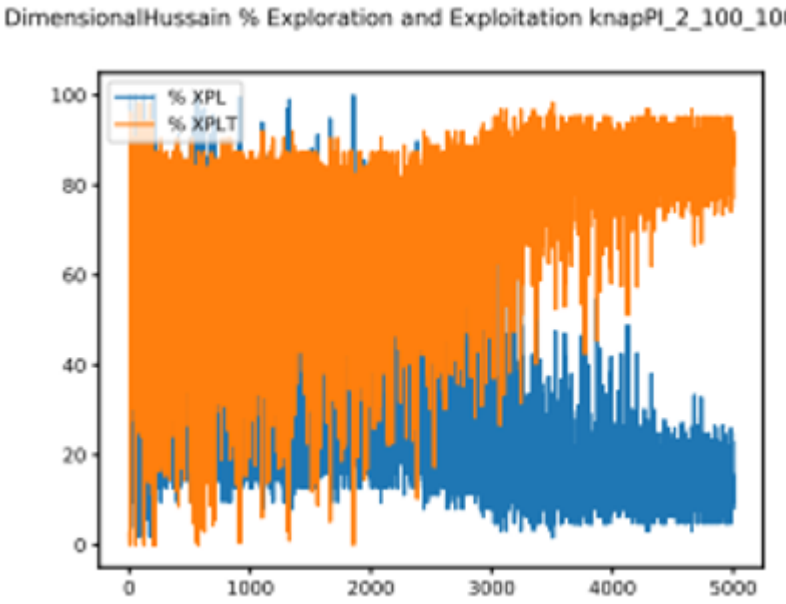


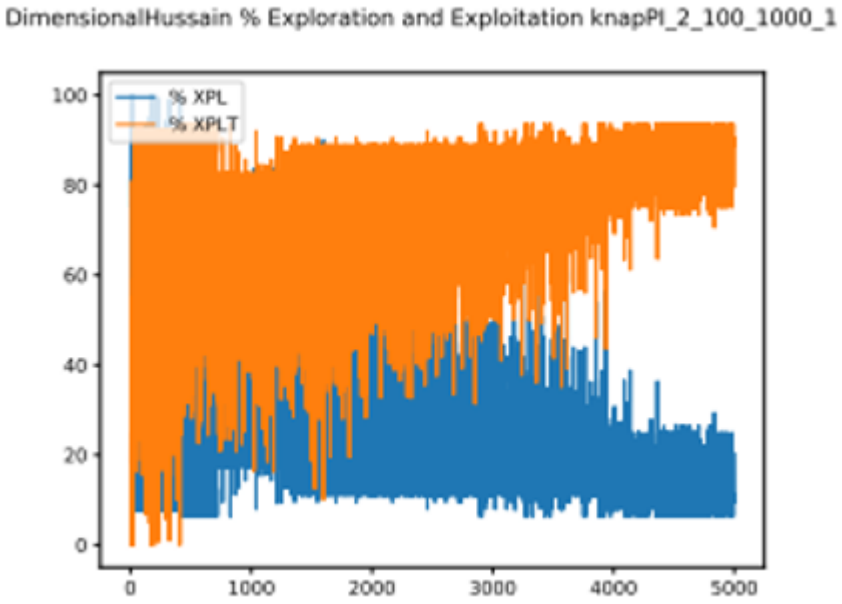
Exploration-Exploitation Graphics of SCP – SCA-BQSA



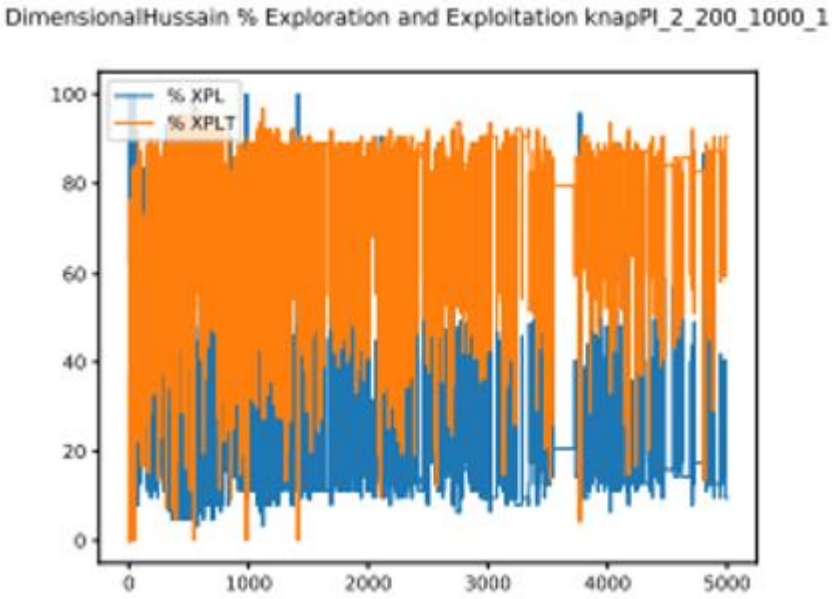


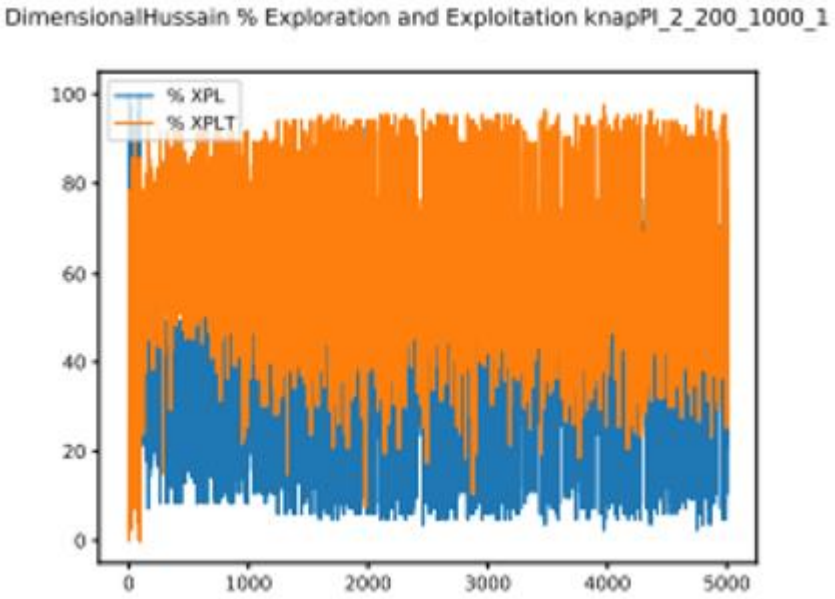
Exploration-Exploitation Graphics of 0-1KP – WOA-QL/WOA-SARSA



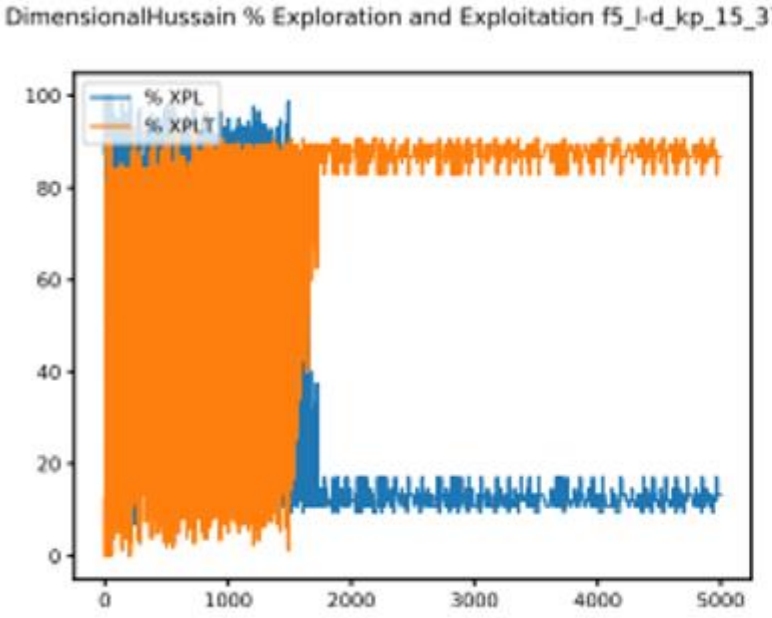


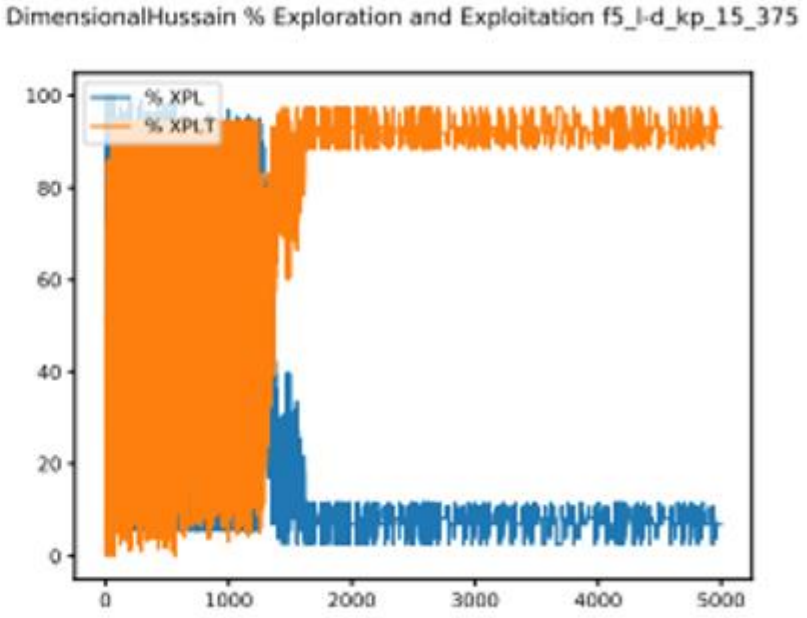
Exploration-Exploitation Graphics of 0-1KP – GWO-QL/GWO-SARSA



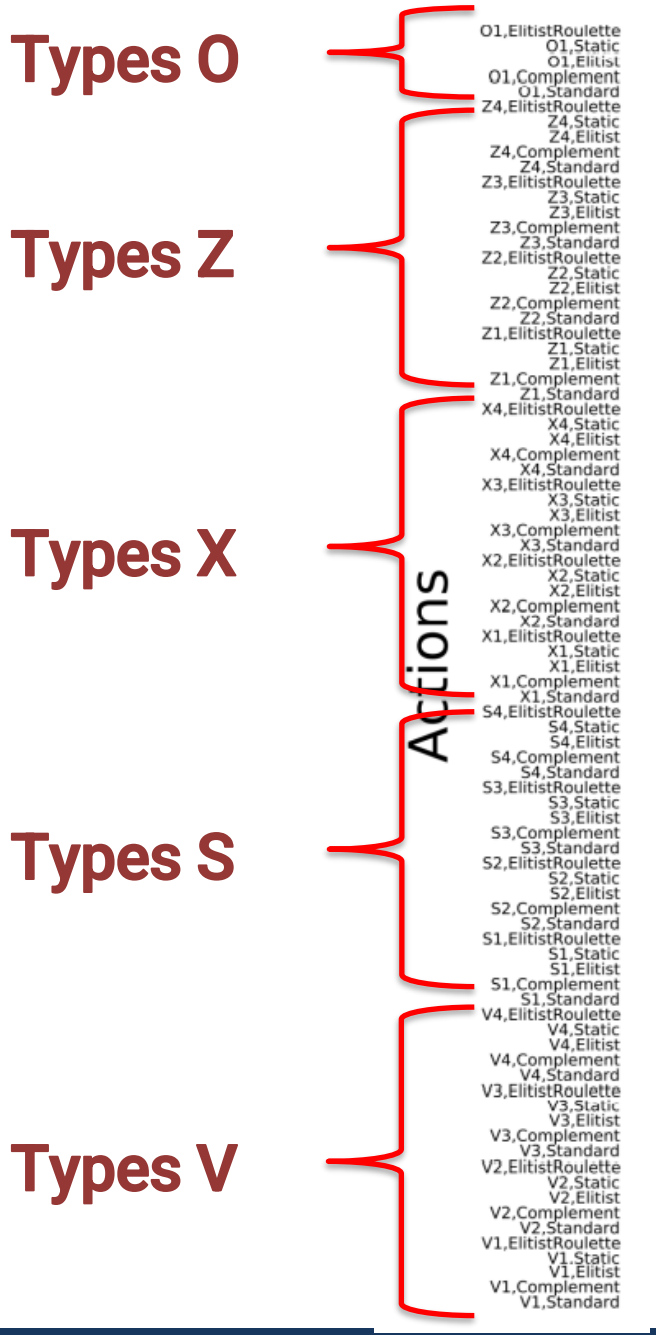


Exploration-Exploitation Graphics of 0-1KP – SCA-QL/SCA-SARSA

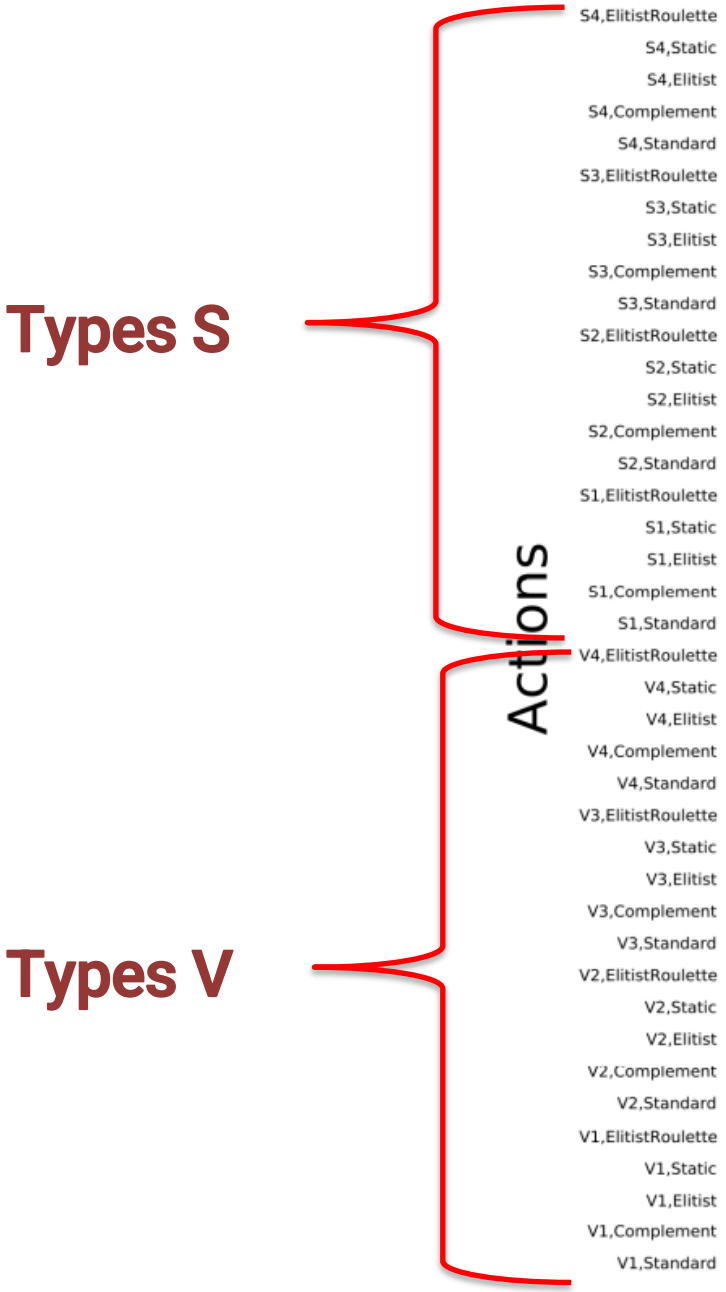




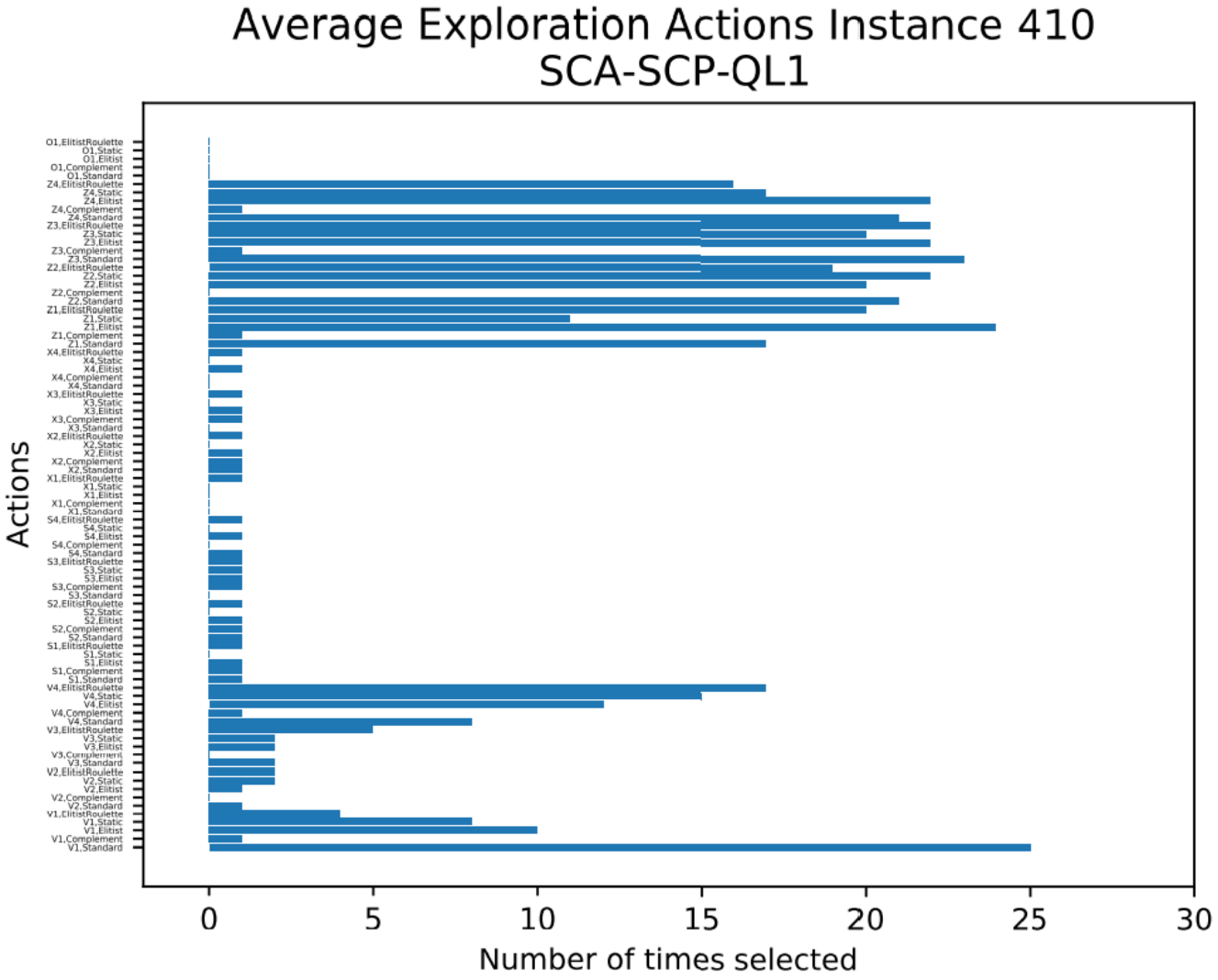
Actions that can be taken



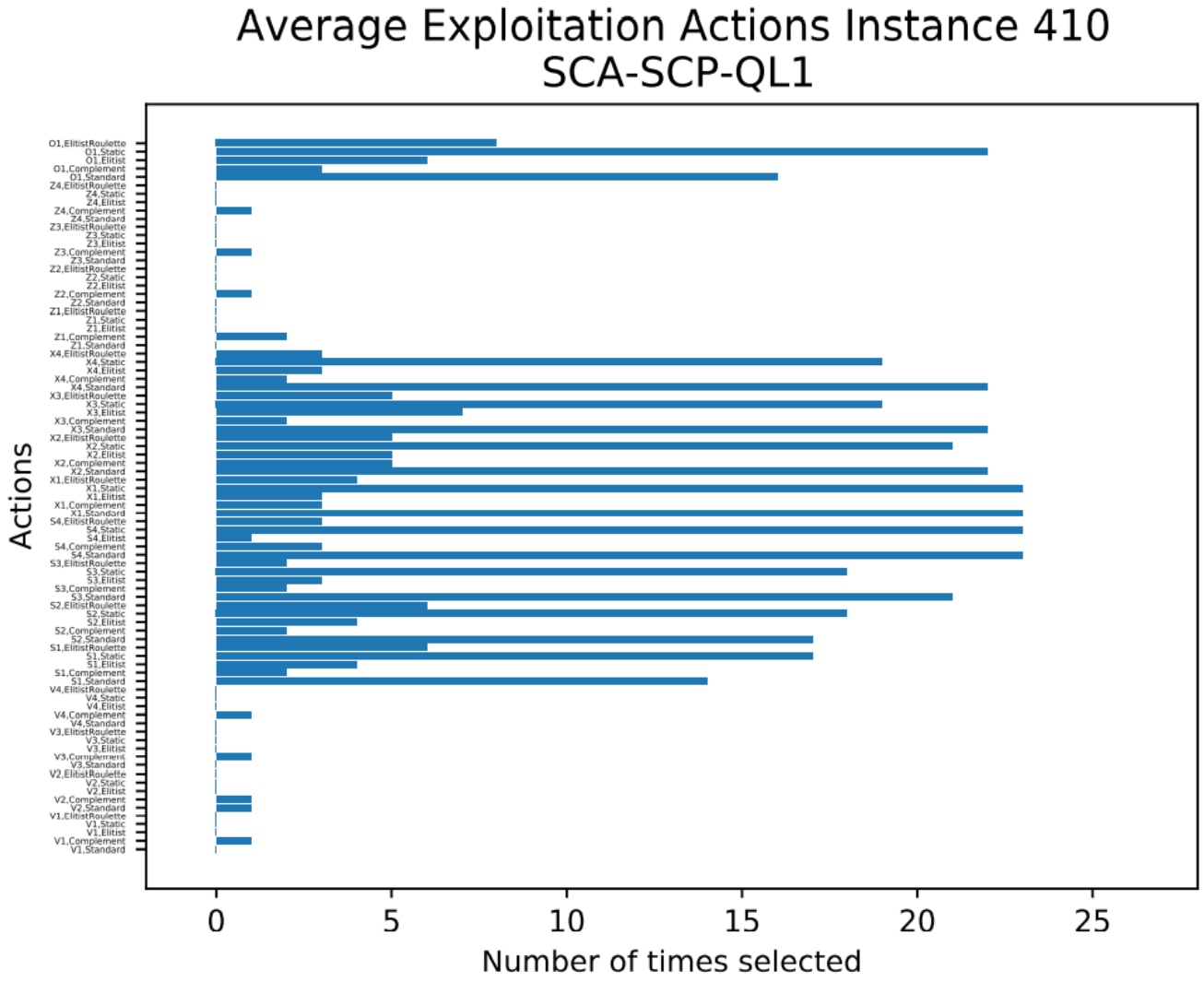
Actions that can be taken



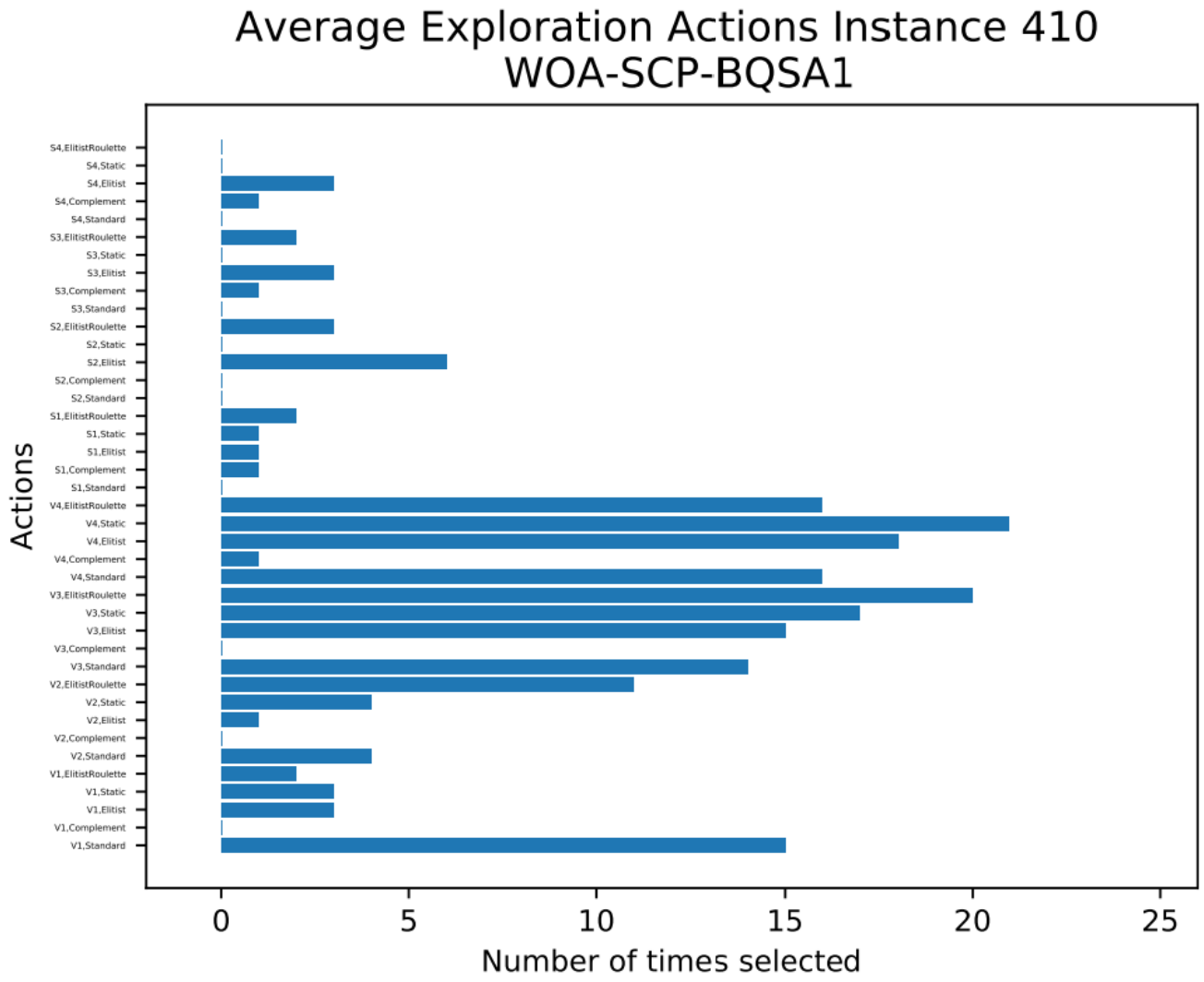
Action Graphics of SCP with 85 actions



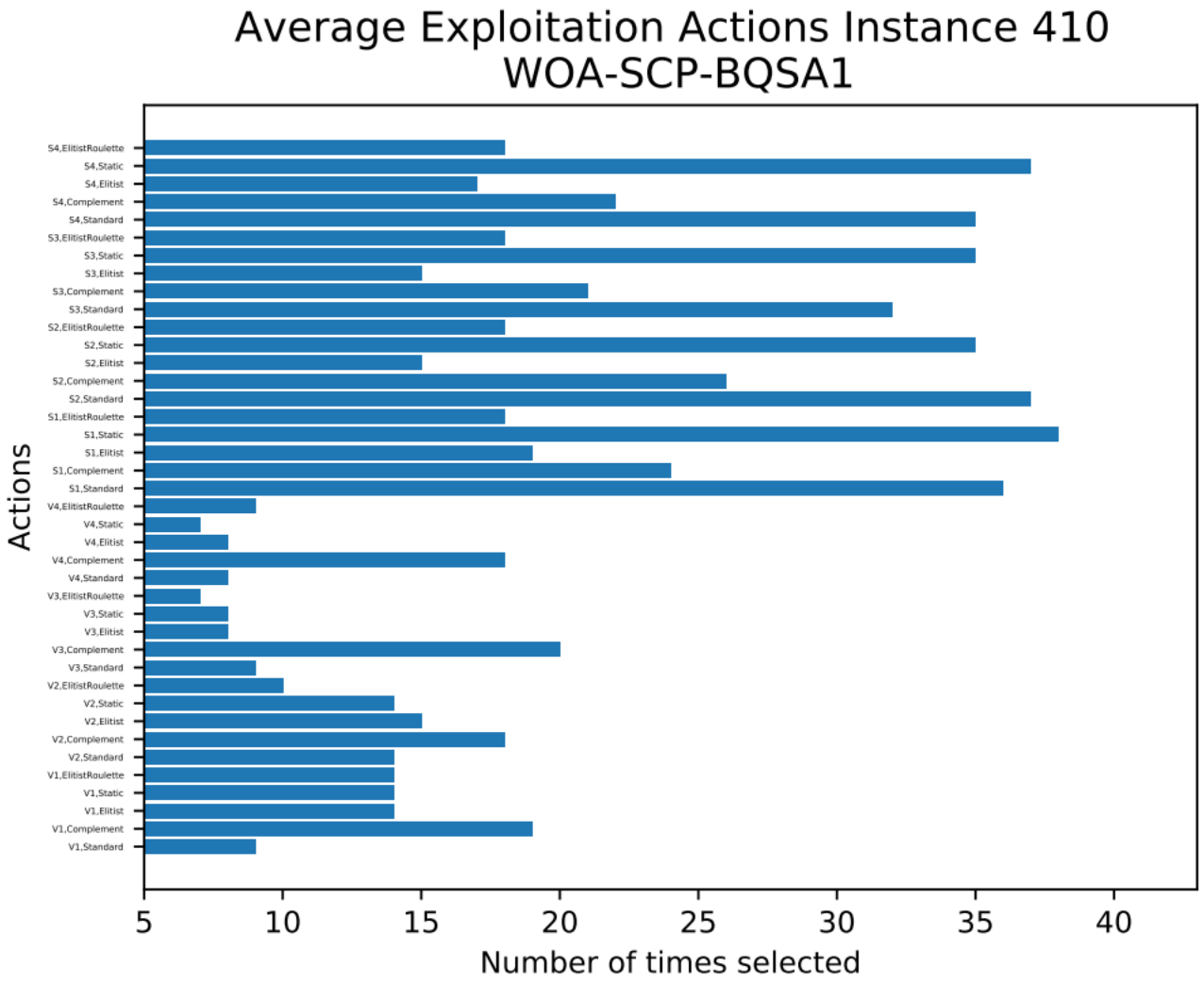
Action Graphics of SCP with 85 actions



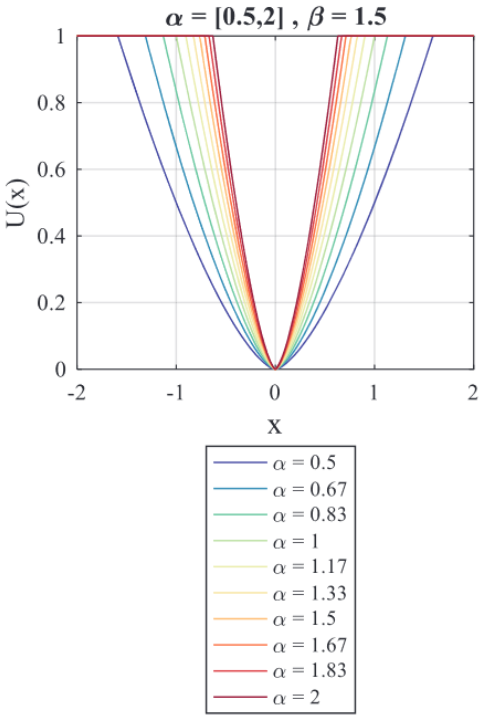
Action Graphics of SCP with 40 actions

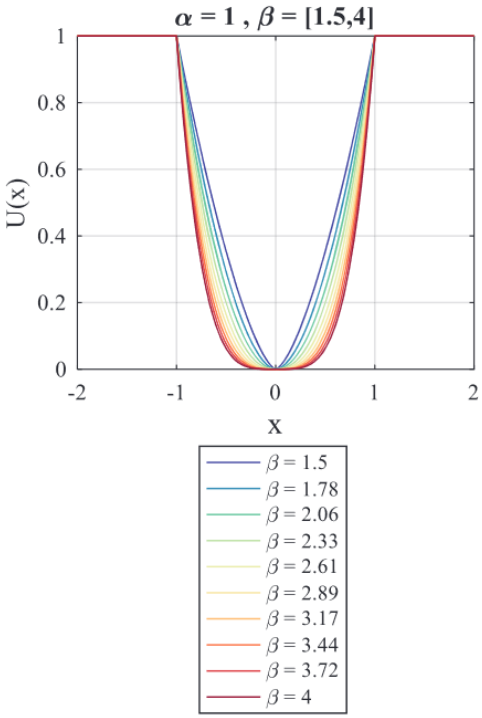


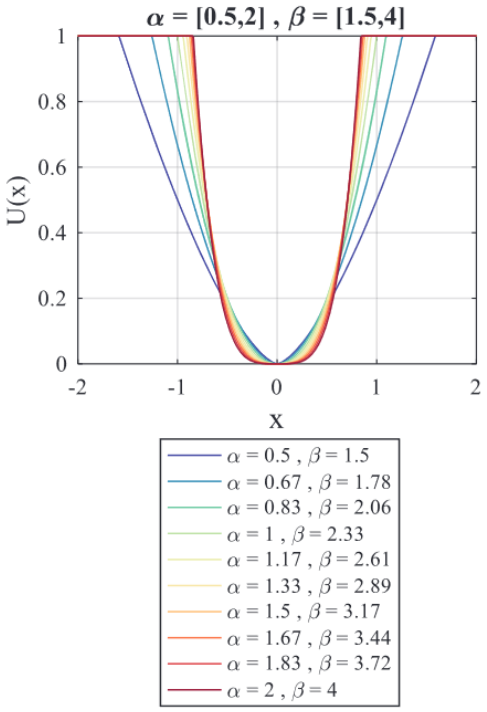
Action Graphics of SCP with 40 actions



U-Shaped



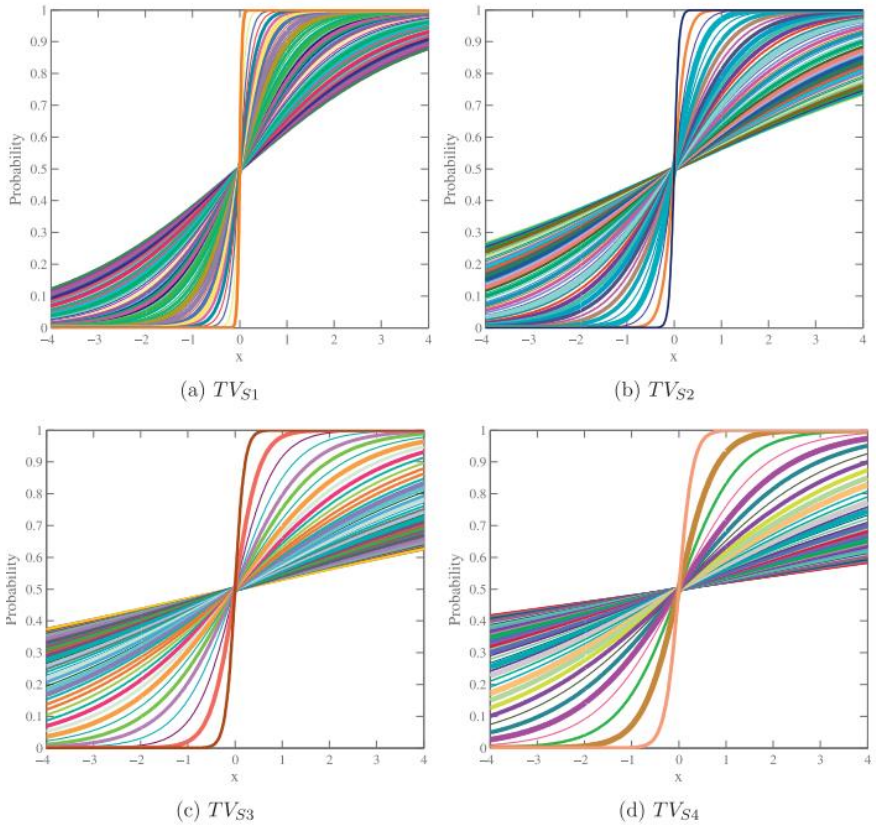


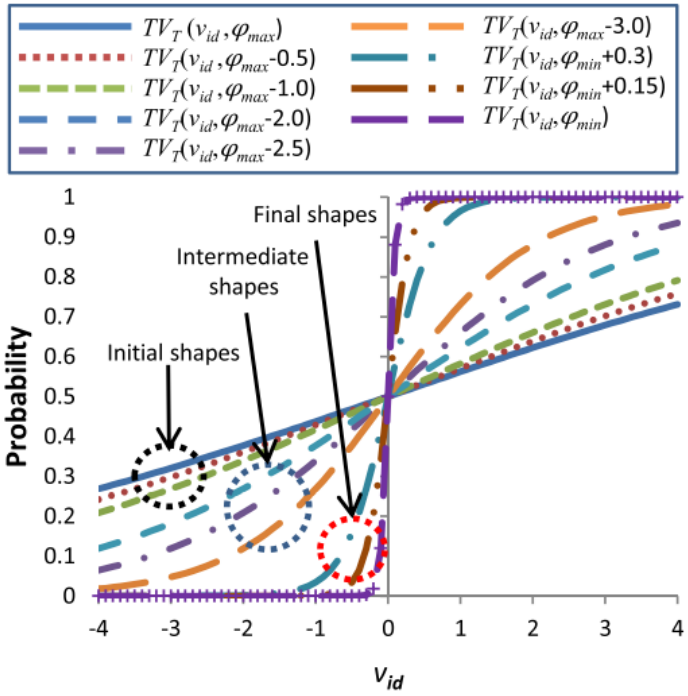


$$U(x) = \alpha |x^{\beta}|$$

Mirjalili, S., Zhang, H., Mirjalili, S., Chalup, S., & Noman, N. (2020). **A Novel U-Shaped Transfer Function for Binary Particle Swarm Optimisation**.

Time Varying

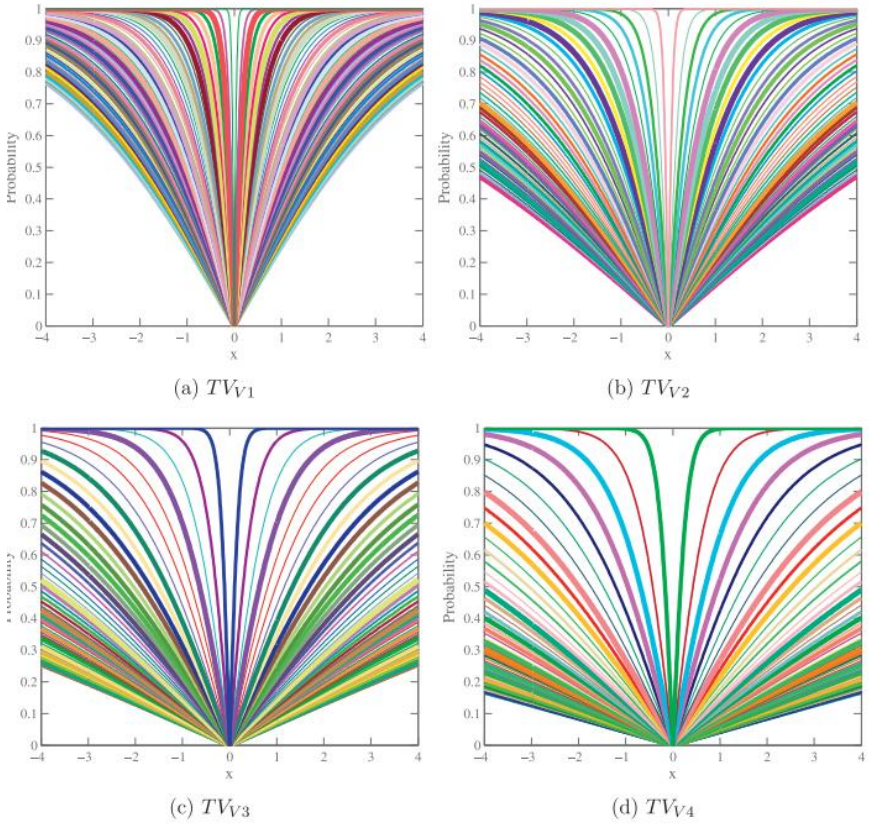




Chantar, H., Thaher, T., Turabieh, H., Mafarja, M., & Sheta, A. (2021). **BHHO-TVS: A Binary Harris Hawks Optimizer with Time-Varying Scheme for Solving Data Classification Problems.**

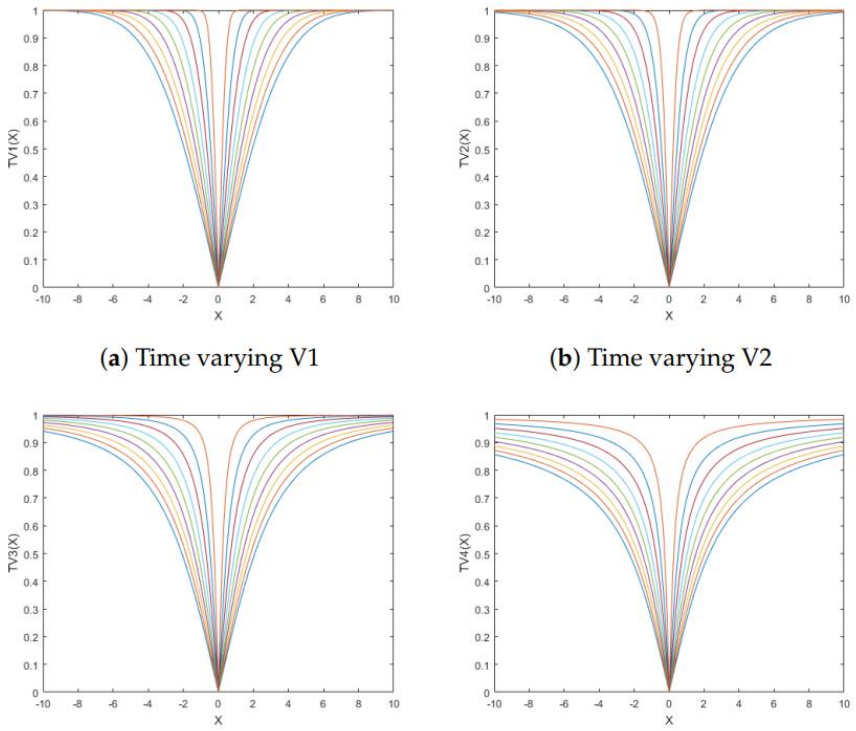
Mafarja, M., Aljarah, I., Heidari, A. A., Faris, H., Fournier-Viger, P., Li, X., & Mirjalili, S. (2018). **Binary dragonfly optimization for feature selection using time-varying transfer functions.**

Time Varying



(a) TV_{V1} (b) TV_{V2}

(c) TV_{V3} (d) TV_{V4}



(a) Time varying V1 **(b)** Time varying V2

(c) Time varying V3 **(d)** Time varying V4

Islam, M. J., Li, X., & Mei, Y. (2017). **A time-varying transfer function for balancing the exploration and exploitation ability of a binary PSO.**

Kahya, M. A., Altamir, S. A., & Algamal, Z. Y. (2021). **Improving whale optimization algorithm for feature selection with a time-varying transfer function.**

Whale Optimization Algorithm (WOA)

For Iter (t):
  For Solución (x):
    For Dimensión (d):
      if $(p < 0.5)$*then*
        if $(|A| < 1)$ *then*
        $Eq.20$
        else $(|A| \geq 1)$ *then*
        $Eq.18$
      else $(p \geq 0.5)$
        $Eq.21$
  $t = t + 1$
Return X^*

$p = [0, 1]$

$C = 2 \cdot r \qquad r = [0, 1]$

$X_d^{t+1} = X^{*t}_d - A \cdot D$

$X_d^{t+1} = X^{*t}_{Rand_d} - A \cdot D$

$X_d^{t+1} = D' e^{bl} \cdot \cos(2\pi l) + X^{*t}_d$

$D' = |X^{*t}_d - X^t_d|$

$A = 2 \cdot a \cdot r - a$

Grey Wolf Optimization (GWO)

For Iter in (t):

$$Set\ a = 2\ - t * \left(\frac{2}{T}\right)$$

For solution in (x):

For dimension in (d):

Update position with Eq. 26

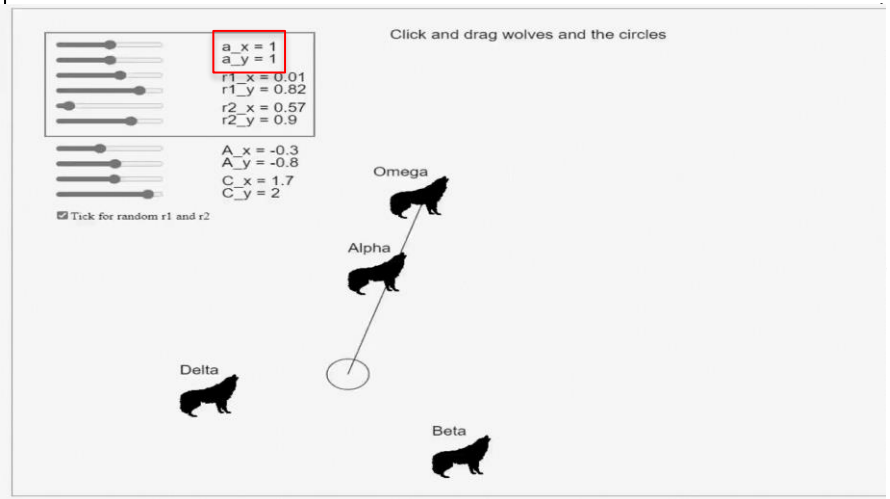
Update A and C

Calculate fitness of population

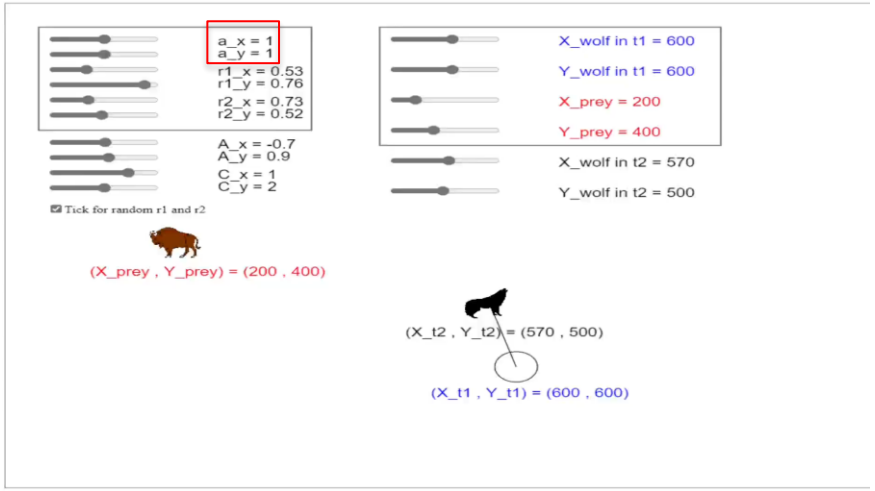
Update $X_\alpha, X_\beta, X_\delta$

$t = t + 1$

Return Best Solution

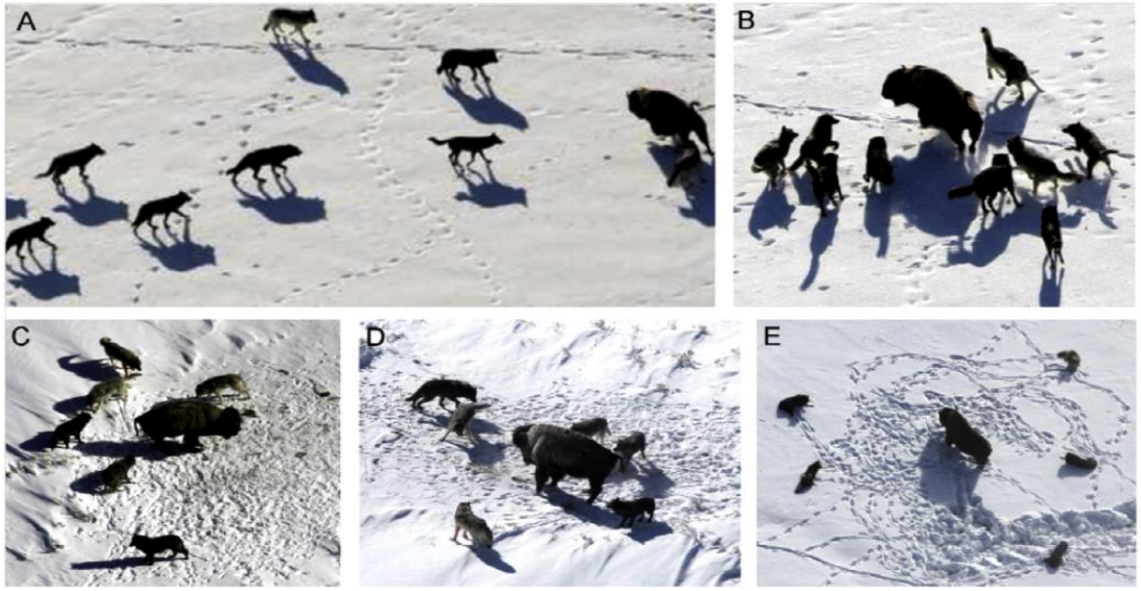


$$v^{t+1} = \frac{X_1+X_2+X_3}{}$$



Grey Wolf Optimization (GWO)

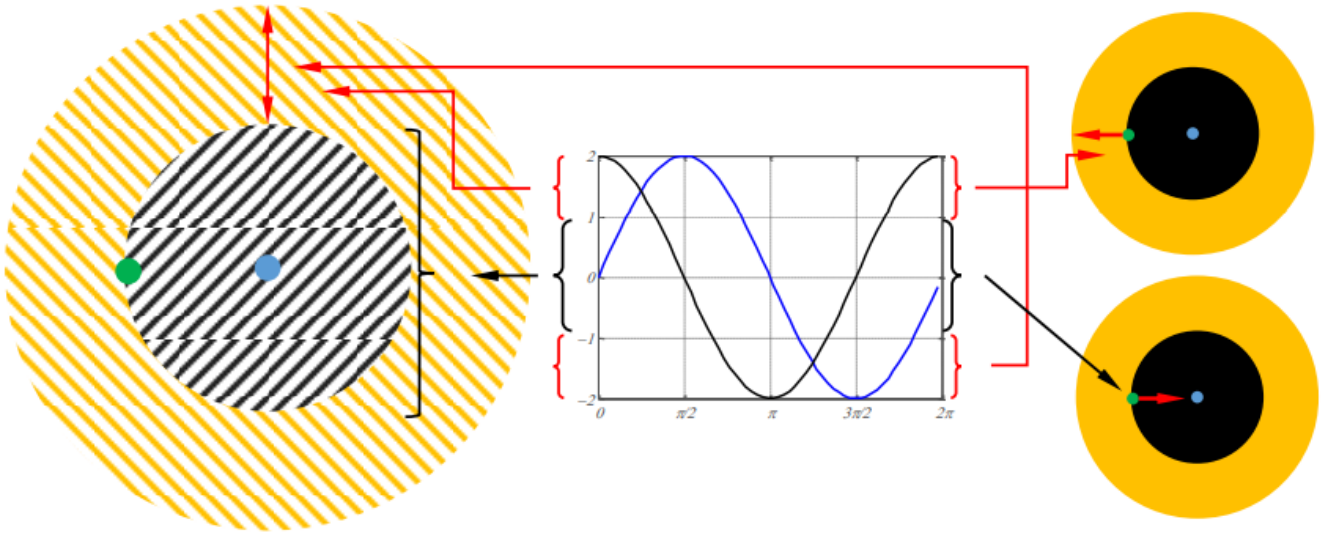
It is a population-based metaheuristic that is inspired by the behavior of gray wolves and their hierarchy when searching for and hunting their prey.



A. Pursuit, approach and tracking
B-C-D. Tracking, harassing and encircling.
E. Atack

Sine-Cosine Algorithm (SCA)

Population-based metaheuristic inspired by the fluctuation that solutions have when following a mathematical model based on sine and cosine functions.



Sine and cosine with the range in [-2,2] allow a solution to go around (inside the space between them) or beyond (outside the space between them) the destination

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Machine Learning

General Q-Learning Equation

Select the maximum action

$$Q_n(s_t, a_t) = Q_{n-1}(s_{t-1}, a_{t-1}) + \alpha[r_n + \gamma \cdot \max_a Q_{n+1}(s_{t+1}, a_{t+1}) - Q_n(s_t, a_t)]$$

Previous value

- Learning factor(α):
  - Indicates the importance of the information previously obtained.
  - $\alpha \in (0,1)$
- Reward(r_n):
  - Indicates the penalty or reward value of the action.
  - $r_n \in \mathbb{R}$
- Discount factor(γ):
  - It functions as a scaling factor to reward or punish in the current action.
  - $\gamma \in (0,1)$

SARSA General Equation

Discount factor

$$Q_n(s_t, a_t) = Q_{n-1}(s_{t-1}, a_{t-1}) + \alpha[r_n + \gamma \cdot Q_{n+1}(s_{t+1}, a_{t+1}) - Q_{n-1}(s_{t-1}, a_{t-1})]$$

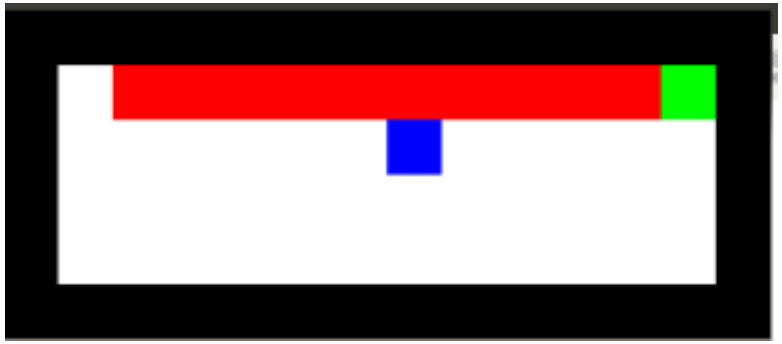
Previous Value | Reward | Value of the following state

- Learning factor(α):
  - Indicates the importance of the information previously obtained.
  - $\alpha \in (0,1)$
- Reward(r_n):
  - Indicates the penalty or reward value of the action.
  - $r_n \in \mathbb{R}$
- Discount factor(γ):
  - It functions as a scaling factor to reward or punish in the current action.
  - $\gamma \in (0,1)$

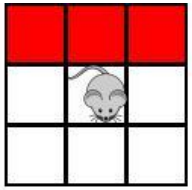
Difference between SARSA and QL

Mouse vs Cliff:

In the present scenario the red squares are shown as a cliff, the blue square as the mouse and the green square as the cheese.



State:



Action values:

W	NW	N	NE	E	SE	S	SW
	-50	-50	-50	+50			

Ejemplo para diferenciar SARSA y QL

Using QL :

Ejemplo para diferenciar SARSA y QL

Using SARSA: