CS3CI Computational Intelligence Solution for Logistics Experimental Study

1. Introduction

This experimental study focuses on implementing a novel computational intelligence solution to predict the daily demand of a logistic company using an artificial neural network model. A baseline solution will also be implemented to be compared against the novel solution in order to identify, with justification, the winning solution. The baseline solution implements a basic Particle Swarm Optimisation (PSO) algorithm and the novel solution implements a PSO with time varying parameters.

2. Proposed Computational Intelligence Solution

The baseline solution implements a basic Particle Swarm Optimisation algorithm, which consist of a set of particles in a swarm moving within the search space, each representing a potential solution. The parameters that control the behaviour of this algorithm, such as the velocity weight and the acceleration constants, are fixed for the duration of the search for this algorithm.

The proposed novel solution implements a Time Varying Particle Swarm Optimisation (TVPSO) algorithm, that uses a dynamic trigonometric function to adjust the inertia weight over time. Additionally, the learning factors, cognitive coefficient and social coefficient are also dynamically adjusted. In the initial stage of the search, the inertia weight is set to a large value and decreases gradually and reaches a small value at the end (Hu et al., 2018). The formula for the inertia weight ω change to decrease non-linearly is:

$$\omega = \alpha + \beta \cdot \cos\,(\pi \cdot \left(\frac{ni}{NI}\right))$$

The performance of the algorithm is adjusted according to the cosine function $\cos x$ and dynamically adjusting inertia weight ω based on the trigonometric function. α and β are adjustment factors; ni and Ni are the current iteration and maximum number of iterations, where in this study. The curve of the inertia weight changes can be seen in Figure 1.

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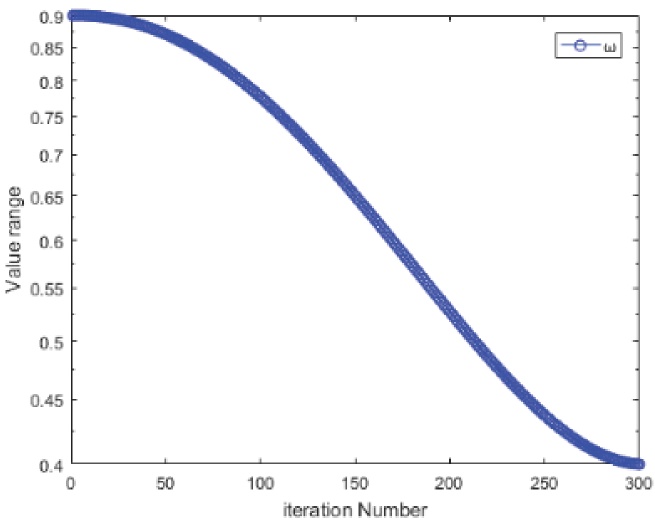

Figure 1. Inertia weight curve (Hu et al., 2018)

From Figure 1, we can observe that ω is given a large value in the beginning of the algorithm to ensure that all particles are set at an relatively large speed step. As the algorithm progresses, the smaller ω value can ensure that the particle can search near the extreme point to provide a greater chance of converging to the global best optimal solution. This can allow the algorithm to avoid getting stuck in local optima. In traditional PSO, the particles can sometimes get trapped in a suboptimal region of the search space, and they may be unable to escape from it. By allowing the parameters of the algorithm to change over time, TVPSO can potentially help the particles escape from local optima and explore other regions of the search space (Hu et al., 2018).

The acceleration parameters c_1 and c_2, cognitive and social coefficients are dynamically adjusted to influence the performance of the algorithm. Learning factors with time varying factors cause particles in the initial stage of the algorithm to have an small social-learning ability, large self-learning ability, and have a strong global search, which is beneficial to converge the global optimal solution (Hu et al., 2018). The two learning factors are calculated by :

$$c_1 = \Upsilon - \frac{\theta \cdot ni}{NI}$$

$$c_2 = \rho + \frac{\theta \cdot ni}{NI}$$

Where ni and NI are the current iteration and maximum number of iterations, Υ, ρ and θ are adjustment factors to be adjusted in this experiment.

As c_1 is given a larger starting value and is dynamically decremented as the algorithm search continues. Furthermore, c_2 is dynamically increased from a low starting value to ensure that the particles can roam far from good regions before being pulled back towards good regions as the search continues. This causes the particles to obtain good individual experiences in the beginning, and in the later stage of the search, the particles move to the global optimal to access each others individual experiences. At then end of the search, c_2 is greater than c_1, causing particles to be more strongly attracted to the global best position, preventing premature convergence (Innocente et al., 2010).

3. Experimental Methodology

Welch's t-test will be incorporated in this experiment to compare the two algorithms and how they perform on evaluating the daily demand of the logistics company based on the demand indicators, which will be measured by the mean squared errors (MSE) each produces. The null hypothesis is that the baseline algorithm, on average, is no better than the novel algorithm on the problem in terms of MSE's produced. The alternate hypothesis is that the novel algorithm, on average, is better than the baseline algorithm on the problem in terms on MSE's produced.

The significance level α is set to 0.05 for this experiment. The problem will be tested 100 times to ensure a broader range of results and to obey the laws of the central limit theorem. The t-test will take the average of both results to produce a p-value to determine whether the null hypothesis will be rejected.

The data from the file 'train.csv' will be used to optimise the parameters using the instance of 'DemandPricePrediction'. Using the unseen data from 'test.csv', the parameters will then be evaluated using a 'DemandPricePrediction' instance to predict the daily demand of the logistics company.

<u>Parameters for baseline PSO:</u>

- Swarm size: 50
- Inertia weight: $1 \div (2(\ln(2))$
- Cognitive coefficient: $0.5 + \ln(2)$
- Social coefficient: $0.5 + \ln(2)$
- Termination condition: 2000

<u>Parameters for novel PSO:</u>

- Swarm size: 50
- Range values of iterations : [0.4,0.9]
- Inertia weight: $0.65 + 0.25 \times \cos\left(\pi \times \left(\frac{current\ iteration}{\text{maximun}\ iterations}\right)\right)$
- Cognitive coefficient: $2.5 - \left(\frac{2 \times current\ iteration}{\text{maximum}\ iterations}\right)$
- Social coefficient: $0.5 + \left(\frac{2 \times current\ iteration}{\text{maximum}\ iterations}\right)$
- Termination condition: 2000

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Experiment Results:

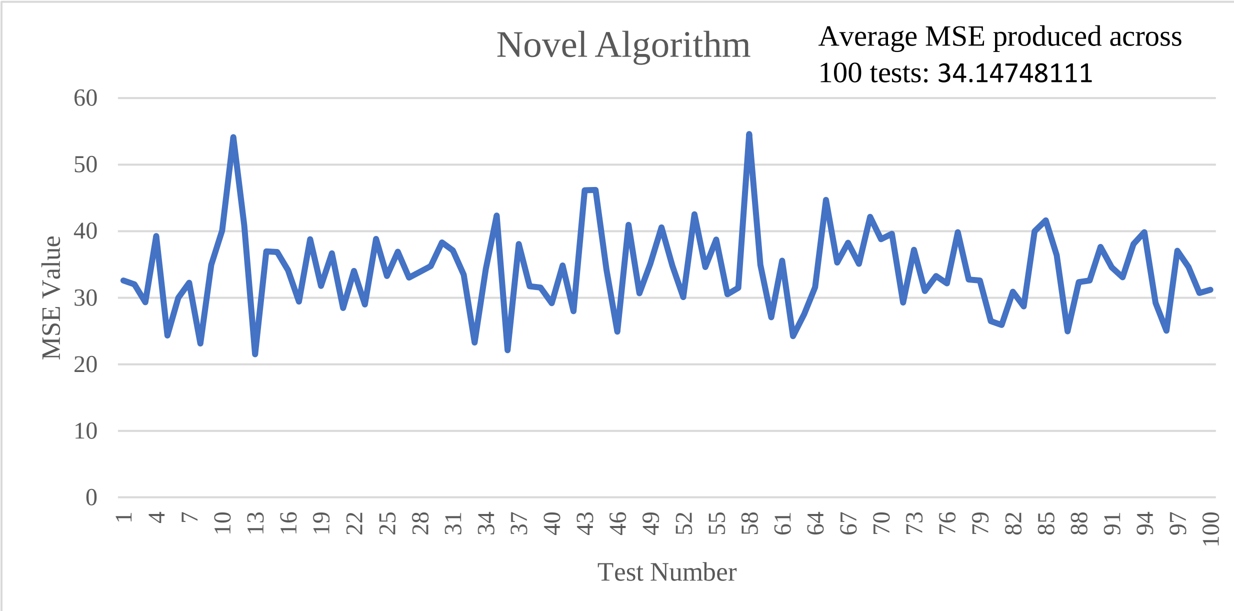

Figure 2. Novel Algorithm Average MSE across 100 tests

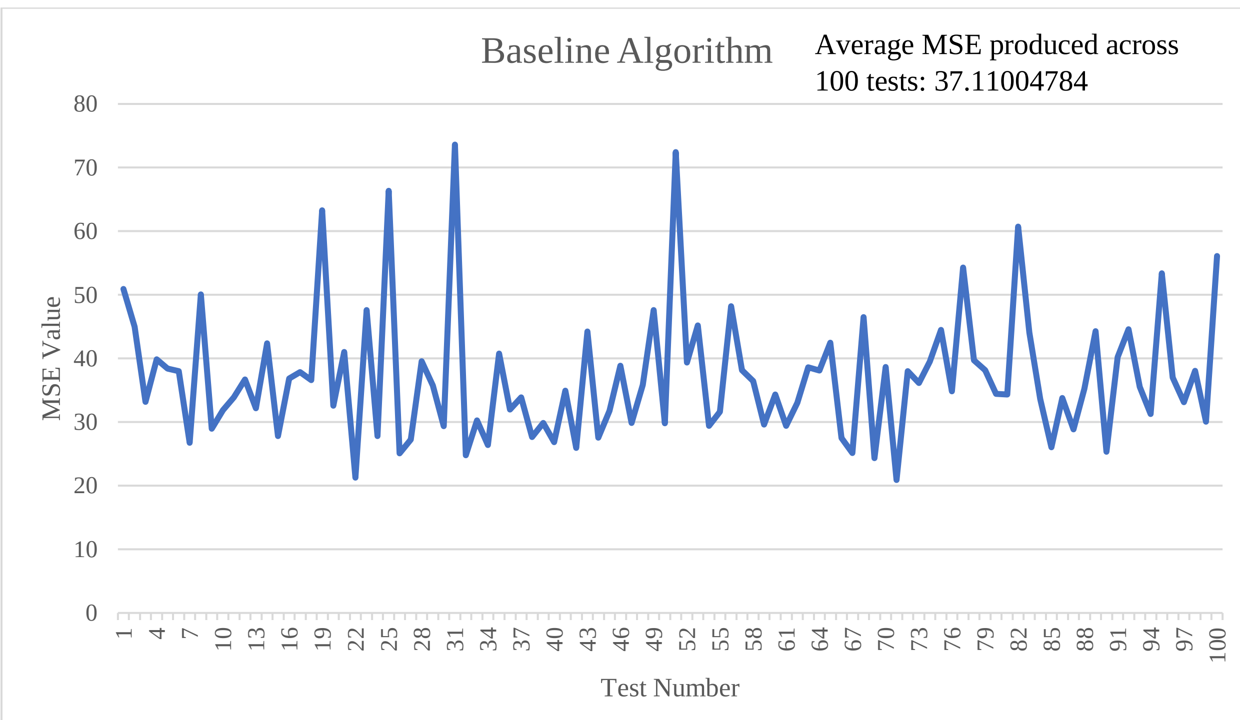

Figure 3. Baseline Algorithm Average MSE across 100 tests

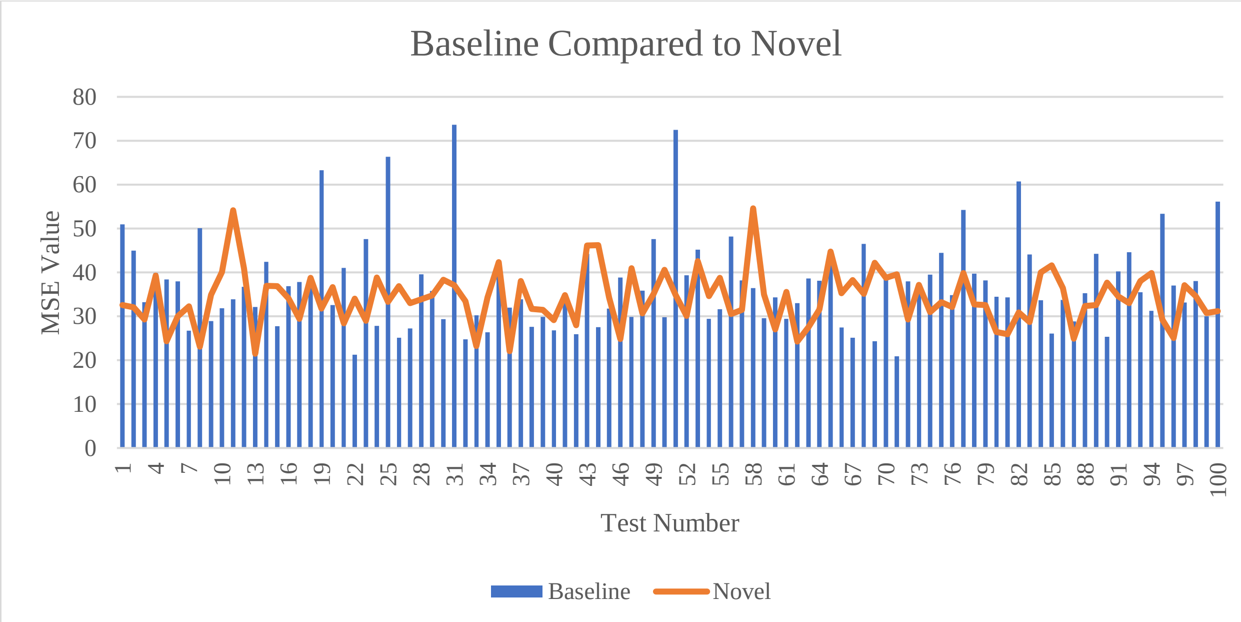

Figure 4. Baseline and Novel Algorithm Comparison

Baseline Algorithm Average	Novel Algorithm Average	Welch's t-test p-value
37.11004784	34.14748111	0.00671687145671919000

4. Analysis of Experimental Results

Implementing Welch's t-test, the p-value results in 0.00671687145671919000, which is less than α (0.05), meaning that there is enough evidence to reject the null hypothesis and to accept the alternate hypothesis.

As seen in Figure 4, the baseline algorithm has a higher chance of producing values that are sub-optimal, whereas the novel algorithm on average produces values that has less major fluctuations. By adjusting the velocity dynamically, it allows the algorithm to adapt to changing characteristics of the search space and adjust the parameters of the algorithm to better suit the changes. However the limitations of TVPSO is that the convergence is slow in the beginning of the test. Because the inertia weight is updated each iteration, it can be difficult to predict the movement of the swarm, making it challenging to tune the parameters of the algorithm to achieve the desired performance (Hu et al., 2018).

In conclusion, the winning solution is the novel algorithm, as the results from the testing data in comparing the two algorithms lead to sufficient evidence in finding parameters to minimise the MSE for predicting demand for the logistics operation.

References

Hu, Z., Zou, D., Kong, Z. and Shen, X., 2018, June. A particle swarm optimization algorithm with time varying parameters. In *2018 Chinese Control And Decision Conference (CCDC)* (pp. 4555-4561). IEEE.

Innocente, M.S. and Sienz, J., 2010. Coefficients' Settings in Particle Swarm Optimization: Insight and Guidelines. *Mecánica Computacional*, *29*(94), pp.9253-926.

Appendix:

Average MSE for 100 tests:

Baseline Solution	Novel Solution
50.93578358	32.56526436
44.97653051	32.020288
33.1925771	29.29682461
39.84210207	39.28892193
38.40219819	24.32009564
38.00017558	29.98119348
26.73224645	32.24657316
50.08852117	23.11608566
28.94850929	34.92449587
31.8673259	40.10637617
33.87010992	54.15172202
36.70388665	40.90097204
32.1468552	21.48659667
42.39534887	36.94622266
27.78688065	36.87534844
36.85008136	34.1028235
37.85181918	29.41591284
36.60864799	38.79063318
63.30300144	31.7427385
32.59108675	36.65843204
41.01491764	28.42496823
21.26780733	34.04834464
47.57775193	28.9680564
27.79463055	38.8172217
66.37195041	33.27259594
25.09142972	36.89561412
27.24941485	33.01280646
39.55276149	33.86908638
29.60991818	34.94715412
34.31608389	27.02797589
29.43119964	35.58625534
33.01901919	24.21515057
38.62545387	27.54753764
38.09817421	31.55859907
42.4807333	44.71776943
27.49287459	35.28585889
25.14352768	38.27367669
46.48344599	35.09702498
24.33880451	42.17424634
38.65118473	38.79689647
20.89439158	39.58523585
37.98514918	29.28124232
36.1519947	37.18293522
39.52131925	30.99226198
44.46634625	33.24922237
34.84188989	32.12718325
54.26827973	39.83289876
39.68987224	32.73743907
38.16110556	32.58582321
34.43080069	26.45322375
34.31336008	25.89400362
60.73089993	30.92155584
44.09208752	28.70857149
33.65381132	40.00920214
26.0571069	41.60989226
33.76211408	36.40299432
28.85250407	24.93222976
35.25669286	32.35780813
44.27452284	32.58358326
25.35902156	37.64752304
40.21466668	34.53158938
44.60307149	33.03928431
35.52001612	38.0450435
31.27277122	39.84819451
53.37579755	29.21767249
36.98657937	25.03805762
33.12518064	37.06733537
38.06216115	34.59537885
30.04313794	30.7198891
56.10451473	31.17535265