

# Knowledge workers mental workload prediction using optimized ELANFIS

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This Presentation aims to summarize the implementation of Algorithms and Techniques to predict the workload of knowledge workers effectively, mentioned by the researchers in the research paper mention below.

Research paper - [https://drive.google.com/file/d/1V4ibh063PpeuK-HjUXKoXoX\\_QLzYyJtj/view?usp=sharing](https://drive.google.com/file/d/1V4ibh063PpeuK-HjUXKoXoX_QLzYyJtj/view?usp=sharing)

# Knowledge workers mental workload prediction using optimized ELANFIS

- The competitive society in the new era calls for more research to improve the well-being of workers as well as to improve their productivity. Knowledge workers face a high mental workload in terms of planning and coordination. One solution is to predict the mental workload of knowledge workers.
- This study aims to optimize the extreme learning adaptive neuro-fuzzy inference system (ELANFIS) by integrating particle swarm optimization into a micro genetic algorithm to predict the mental workload of knowledge workers. Although the adaptive neuro-fuzzy inference system (ANFIS) shows reasonable prediction performance, it also suffers from the curse of dimensionality and has a poor computation time.
- Two types of data were used for this study. One was data collected through questionnaires issued to the participants to assess their subjective experience of the task load (NASATLX) in terms of mental requirements, their emotions, and their stress levels, and the other type was data collected through sensors, for example, “computer interactions, via a computer logging tool; facial expressions, via a webcam; body postures, via a Kinect 3D camera; and physiology (ECG and skin conductance), via body sensors”

# ELANFIS without optimization

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## Algorithm 1: Pseudocode of ELANFIS

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```
1: Set the number of membership functions (h) and the number of iterations
2: for i=1:iteration do
3:   for j=1:input do
4:     for k=1:h do
5:       Randomly select premise parameters ( $a_{jk}$ ,  $b_{jk}$ , and  $c_{jk}$ )
6:     end for
7:   end for
8:   Given training data,  $(x_p, y_p) \in \mathbb{R}^n \times \mathbb{R}$  ( $p = 1, 2, \dots, N$ ), find the matrix H
9:   Calculate the consequent parameter matrix  $\beta$ 
10:  Calculate the network output using obtained parameters  $\beta$  and H, and
11:  compute the MSE
12: end for
```

- ELANFIS incorporates the ELM concept to tune the premise parameters of the fuzzy rules in the ANFIS architecture.
- It also has the capability of qualitative knowledge representation. Increasing the number of membership functions of the input variables in the ELANFIS model will increase the accuracy. In comparison to ELMs, the randomness in ELANFIS is decreased due to the embedding of explicit knowledge.
- There have been many successful applications of ELANFIS, especially for model predictive control (MPC) and inverse control of nonlinear systems.
- However, when the number of inputs is high, there will also be a large number of rules and it will suffer from the curse of dimensionality. Thus, it has to be optimized with algorithms discussed below.

# ELANFIS optimized with PSO Algorithm

## Algorithm 1: PSO Algorithm

```
1: Generate initial population P of size N
2: While i < Maximum Evaluation
    Update velocity and position of population
3: end while
   Termination criteria satisfied
```

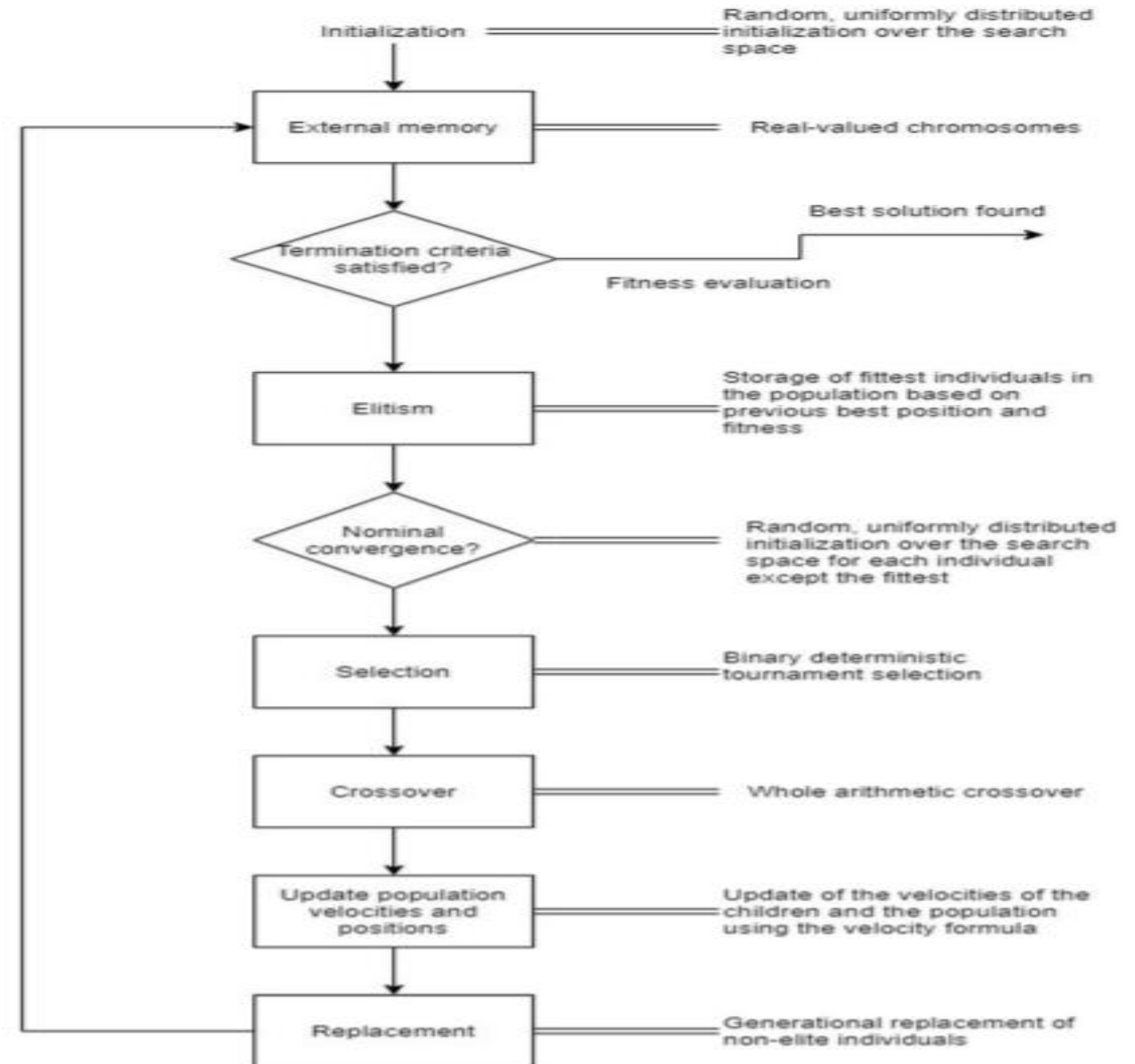
- For comparison with the proposed method of predicting mental workload, we consider ELANFIS optimized with particle swarm optimization. It is effective in locating promising areas of the search space to find better solutions at a faster rate.
- The outline of PSO is as follows:
  1. A sufficient set of PSO parameters (a probable solution to the optimization problem of interest) is coded. In addition, a fitness function is developed based on the given objective function. Each binary string is known as a chromosome, and its features are called genes.
  2. The velocity and position of each member of the population are updated. Thus, the whole generation is replaced with a new generation.
  3. When the termination criteria are reached, the algorithm terminates and returns the best solution.

# ELANFIS optimized with mMGA

## Algorithm 1: Modified micro-genetic algorithm

```

1: Generate initial population P of size N and store contents in population
   memory M
2: While i < Maximum Evaluation
   Termination criteria satisfied
3:   Apply elitism
4:   If converge
5:     Initialize 4 new individuals
6:   End if
7:   Binary tournament selection
8:   Whole arithmetic crossover
9:   Update velocities of individuals and the population
10:  Produce the next Generation
11: end while
  
```



# Proposed model to predict mental workload

- In the above method, the advantages of both, Particle swarm optimization and a micro-genetic algorithm are combined into one. When the two algorithms are integrated, the resulting algorithm can locate promising areas of the search space and find better solutions at a faster rate. This is Modified Micro Genetic algorithm(MmGA).
- The results of this study show that the optimization of ELANFIS using the proposed MmGA produces far better performance than that of ELANFIS without optimization, with improvements in the MSE and RMSE for regression, and even surpasses the optimization of ELANFIS achieved using PSO alone.
- Besides is the flowchart of the proposed model.

