Design a Non-Linear Conical Tank System with Continuous Tuning and Adaptive Fractional Order PID Controller

A. RAJENDRAN[1*], M. KARTHIKEYAN[2], G. SARAVANAKUMAR[3]

Assistant Professor[1], Professor[2, 3]

Department ofECE, Amrita College of Engineering and Technology, Nagercoil[1]

Tamilnadu College of Engineering, Coimbatore[2,3]

Abstract:

The proposed research idea is to design a continuously tuned adaptive Fractional order PID controller for a non-linear conical tank system. An adaptive auto tuning approach will be implemented to continuously tune the controller parameters in correspondence with the change in operating points. For each stable operating point, a FOPTD model will be identified using process reaction curve method. The estimated model parameters are used to calculate the controller parameters for each operating points. Based on these calculated controller parameters and its operating points, a tuning system will be designed. The tuning system will be able to interpolate and extrapolate the relation between control variable and the controller parameters over entire span of control variables. Finally, a detailed time-domain modeling of the conical tank will be performed. Microcontroller based DAQ to interface the simulink tool with the system. Thus the adaptive controller will be able to produce a consistent response regardless of parametric variations with minimum overshoots, minimum settling time, and minimum tuning parameters to obtain a critically damped system.

Keyword: *FOPID, PID, Optimization, Fuzzy, PSO.*

INTRODUCTION:

In this research work based on the Computer based controller used in industries. When compared to Existing control systems availed in for industrial applications, controller has been relied ahead for machine control just about as long as other control [1].The following are the existing methods are being used in earlier days, as follow;Switched Logic control, Relay based Logic control, Processor based controllingsystem, Microcontroller based controllingsystem, PLC based control method.

PROBLEMS FACED IN EXISTING METHOD:

- Many control relays can be replaced by software, which means relay logic controller produce more hardware failure.
- Particularrole such as delay time, counter and timer are not simple to create in software.

PROPOSED METHOD:

Proposed method is PC based control method. Advantage of the PC based control method is,The PC based design for a single task and is equipped with just enough processing power

 https://doi.org/10.37896/pd91.4/91438

to platform that task. Comparing this with the typical PC computing capability and there really is no comparison.

FRACTIONAL ORDER PID CONTROLLER: Process control industries have been using the Proportional Integral Derivative since many decades of years. The ease of design and better recital makes the PID controller wide range popular. Less value of maximum peak overshoot and tinymanipulated value of settling time are plays an important role in popularity of PID controller. In spite of being very popular in industries it also has some limitation of these controller, continuous attempt had been in use to develop the recital, robustness of PID based controller [2]. Due to advancement in the area of fractional calculus expands in the area of generation of PID controller which is universallycalled as fractional order $PI^{\lambda}D^{\mu}$orPIDcontroller. This new PID controller i.e. FOPID controller is an elaborated version of the classical PID controller. The fractional order controller has the advantage to show the resistivity in the change of parameters of control system and controller.The generalize equation of the output task of FOPID based controller is prearranged by,

$$C(s)= \frac{V(x)}{E(x)} = \frac{K_i}{s^{\lambda}} + K_D S^{\mu}$$

Where,
C(s)=controller output
V(s)= Control signal
E(s)= Error signal
K_P= Proportional constant gain
λ= Integration order
μ=order of differentiation

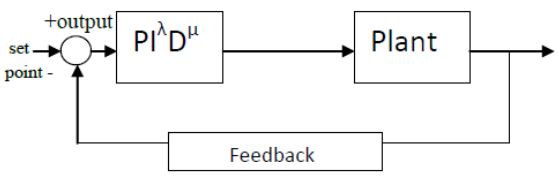

Fig 1.1 Simple Block of FOPID Controller

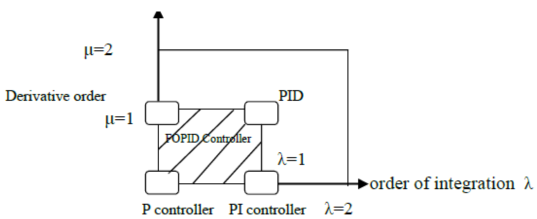

Fig 1.2 Fractional PID

In the fractionalorder PID controller (FOPID), the values of power of I and D are usually kept in the fraction. Consequently, the parameters of constants K_P, K_I, $K_D$can be allotted with two more constraints namely (λ) order of the fractional integration and (μ) fractional derivative. Find out an optimal value of K_P, K_I, K_D, λ and μ, for maintain the desired value of the user. Its need parameter optimization, these are done in various aspects.

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VARIOUS OPTIMIZATION METHODS:

The various optimization methods are

- Particle Swarm Optimization
- Fuzzy Logic Optimization
- Nelder mead optimization

PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimizationis computationaltechniquemeant for optimization of uninterrupted nonlinear operations. Theperformance of one hypothesis is discussed in further detail, followed by grades obtained as of applications and tests ahead which the hypothesis has been shown to achieveeffectively. PSO has sources in few majormoduletechnologies.

It is also associated, however, to traditional calculation, and has equal togetherof GA and evolutionary indoctrination. This project discusses application of the algorithm to the training of artificial neural network weights; Particle swarm optimization has also been demonstrated to perform well on genetic algorithm test functions.

All solution in PSO can be represented as particle in a swarm. Eachparticle has a position and velocity vector and each position coordinate represent a parameter value. Similar to the most optimization techniques, PSO requires a fitness evaluation function relevant to the particle's position. $X_{PB}$and X_{GB} are the personal best position (P_{best}) and global position (G_{best}) of the i^{th}particle. Each particle is initialized with a random position and velocity. The velocity of the each particle is accelerated towards the global best and its personal best positions.

The suitability of individual layer and points are computed. If any suitability is more r than g_{best} , then the new-fangled point befallin g_{best}, and the particles are speed upon the way to new-fangledend. If the particle robustnessimportance is more than p_{best} then $p_{best}$is to be substitute by the present point.

$$V_i(new) = w \times V_i(old) + c_1 \times rand() \times (X_{PB} - X_i) + c_2 \times Rand() \times (X_{GB} - X_i)$$

Here rand() and Rand() are random numbers in the range; c1 and c2 are the acceleration constants and w is the inertia weight factor. The parameter w helps the particles coverage to G_{best} rather than oscillating around it. Suitable selection of w provides a balance between global and local explorations. The flow chart of the PSO is shown below.

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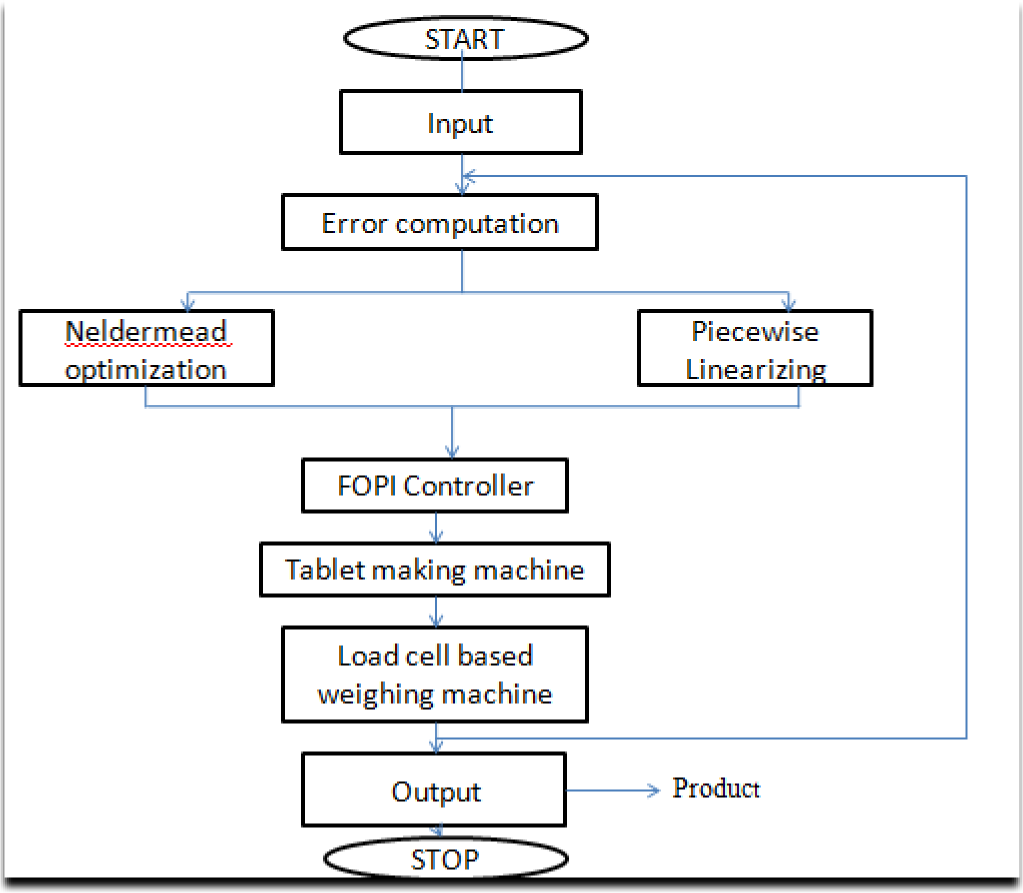

Fig 1.3 Flow chart of PSO controller design procedure

GEOMETRICAL ILLUSTRATION OF PSO:

The update velocity for particles consists of three components. Consider a movement of a single particle in a two dimensional search space.

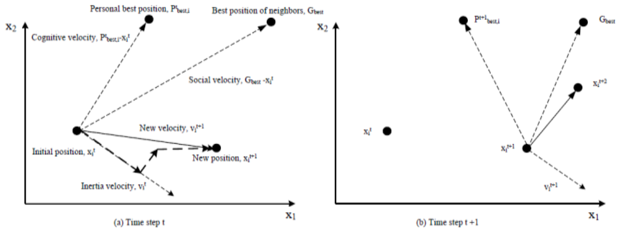

Fig 1.4Particle movements

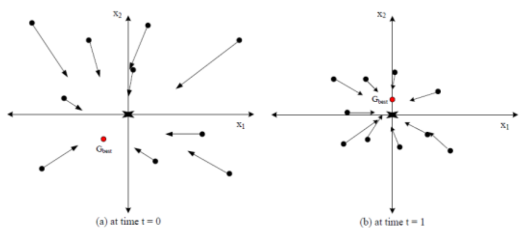

Fig 1.5 Particle positions

Figure illustrates how the three velocity components contribute to move the particle towards the global best position at time steps t and t+1 respectively.Figure shows the position updates for more than one particle in a two dimensional search space and this figure illustrates the gbest PSO. The optimum position is denoted by the symbol ‘ ’. The initial position of all particles with the global best position. The cognitive component is zero at and all particles are only attracted toward the best position by the social component. Here the global best position does not change the new positions of all particles and a new global best position after the first iteration i.e. at t=1.

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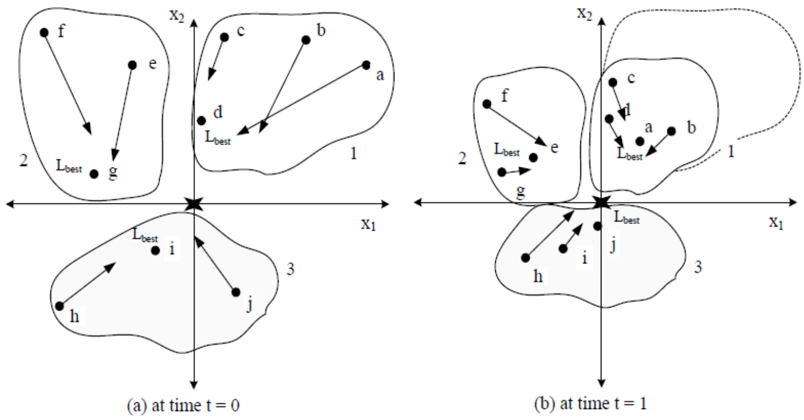

Fig 1.6 Velocity and Position update for Multi-particle in lbest PSO

Figure illustrates how all particles are attracted by their immediate neighbors in the search space using lbest PSO and there are some subsets of particles where one subset of particles is defined for each particle from which the local best particle is then selected. Particles *a*, *b* and *c* move towards particle *d*, which is the best position in subset 1. In subset 2, particles *e* and *f* move towards particle *g*. Similarly, particle *h* moves towards particle *i*, so does *j* in subset 3 at time step. For time step, the particle *d* is the best position for subset 1 so the particles *a*, *b* and *c* move towards *d*.

NELDER MEAD OPTIMIZATION:

The other name of the Nelder Mead Optimization is simplex search algorithm.A simple method for finding a local minimum of a function of several variables has been devised by Nelder and Mead. For two variables, a simplex is a triangle, and the method is a pattern search that compares function values at the three vertices of a triangle. The worst vertex, where $f(x, y)$ is largest, is rejected and replaced with a new vertex. A new triangle is formed and the search is continued. The process generates a sequence of triangles (which might have different shapes), for which the function values at the vertices get smaller and smaller. The size of the triangles is reduced and the coordinates of the minimum point are found.

The algorithm is stated using the term *simplex* (a generalized triangle in *N* dimensions) and will find the minimum of a function of *N* variables. It is effective and computationally compact.The iterative optimization procedures generally use only a starting point x1 ∈D, chosen by specific rules. Contrary, the NP algorithm considers a no degenerate simplex inside the domain D ⊂Rm as starting figure. At every iteration step the NP algorithm modifies a single vertex of the current simplex by applying a λ-transform. In this way it results another no degenerate simplex. More precisely, for any two points y ∈Rm and z ∈Rm we can produce a new point w ∈Rm by using a λ-rule, that is

 https://doi.org/10.37896/pd91.4/91438

ISSN: 0369-8963

$w = z + \lambda (y - z), \lambda \in R$ (3)

So, if $y = (y1,y2,y3,...,ym)$, $z = (z1,z2,z3,...,zm)$, $w = (w1,w2,w3,...,wm)$

We get $wj = z j + \lambda(y j - z j)$, $1 \leq j \leq m$ (4)

Depending on the value of the coefficient λ , $\lambda \in \{\alpha ,\beta ,\gamma ,\delta \}$, and also on the individual significance of the points y and z , we can simulate more geometric type operations as a α-reflection, a β-expansion, a γ-contraction or a δ-shrinkage.

The classical Nelder-Mead algorithm [5] has a lot of little modified forms. For the present study it was implemented in Matlab the variant given in [3]. This variant operates with the following λ parameters:$\alpha = 1$ $\beta = 2$ $\gamma = 0.5$ $\delta = 0.5$

ONE INTERACTION OF THE NELDER ALGORITHM:

1. **Sort.** Evaluate f at the n+1 vertices of _ and sort the vertices so that (1.2) holds.

2. **Reflection.** Compute the reflection point **x**rfrom**x**r= .**x** +α(.**x** −**x**n+1). Evaluate fr= f (**x**r). If f1 ≤ fr<fn, replace **x**n+1 with **x**r.

3. **Expansion.** If fr<f1 then compute the expansion point **x**efrom**x**e= .**x** +β(**x**r− .**x**) and evaluate fe= f (**x**e). If fe<fr,replace**x**n+1 with **x**e; otherwise replace **x**n+1 with **x**r.

4. **Outside Contraction.** If fn≤ fr<fn+1, compute the outside contraction point **x**oc= .**x**+ γ (**x**r− .**x**) and evaluate foc= f (**x**oc). If foc≤ fr,replace**x**n+1 with **x**oc; otherwise go tostep6.

5.Inside Contraction.

If fr ≥ fn+1, compute the inside contraction point xiCxic = ¯x− γ (xr − ¯x) and evaluate fic = f (xic). If fic<fn+1, replace xn+1 with xic; otherwise, go tostep 6.

6. Shrink. For 2 ≤ i ≤ n+1, definexi = x1 + δ(xi −x1).

BLOCK DIAGRAM DESCRIPTION:

The block diagram for the advanced optimization techniques for slurry based control in industrial application is shown below.

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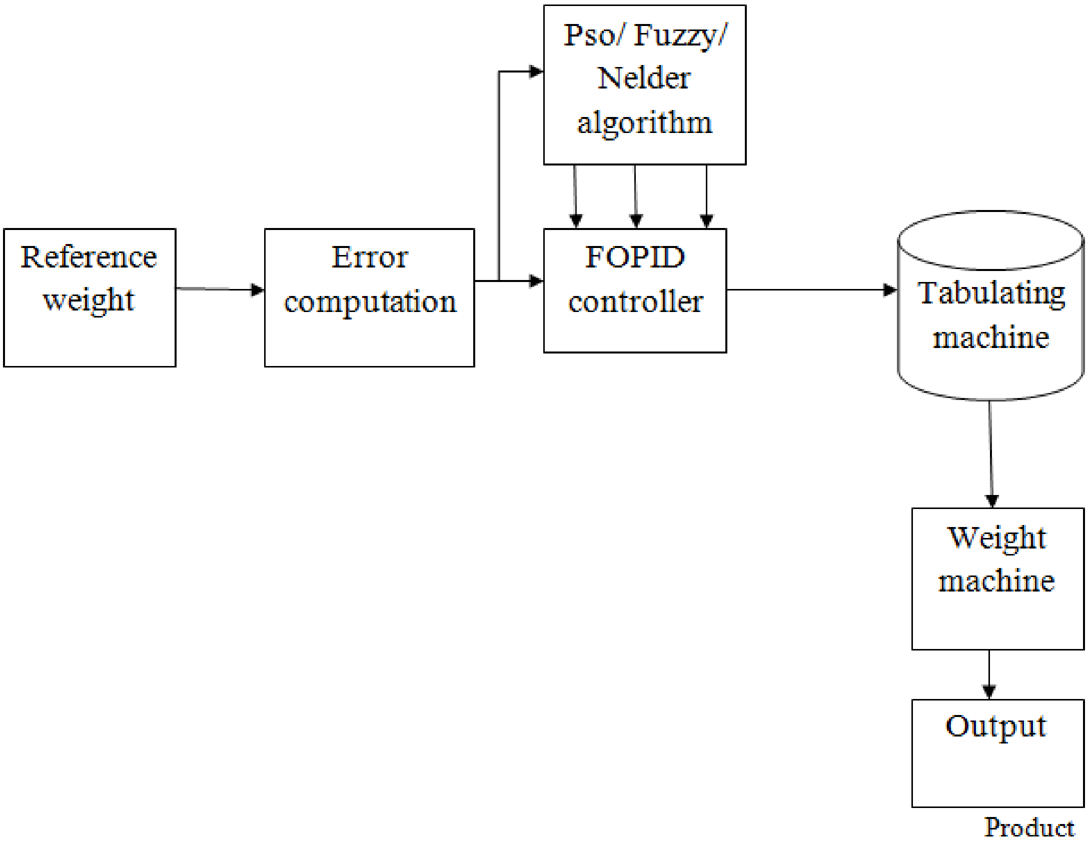

Fig 3.1 Block diagram

BLOCK DIAGRAM EXPLANATION:

The sequence of bit stream data is given to the input. That data is optimized by using three optimization techniques. That is Particle swarm optimization, Fuzzy logic and Nelder mead optimization. The optimized value will give Kp,Kd,Ki values. That value is then given to the controller. The controlled value is then given to the Tabulating machine and then the output is get.The output value is also a bit sequence. And the output value is in constant value. Then the process is correct. But the Random output is get means the process is repeated.

FUZZY OPTIMIZATION:

Fuzzy logic is an approach to computing based on “degrees of truth” rather than the usual true or false. Boolean logic on which the modern computer is based Fuzzy interference is used when the contrast is high then the focus is also high. If contrast is low then focus is low. The output of Fuzzy Optimization the oscillation is very high.Such optimization problems are usually well formulated by crisply specific objective functions and specific system of constraints, and solved by precise mathematics. Unfortunately, real world situations are often not deterministic.

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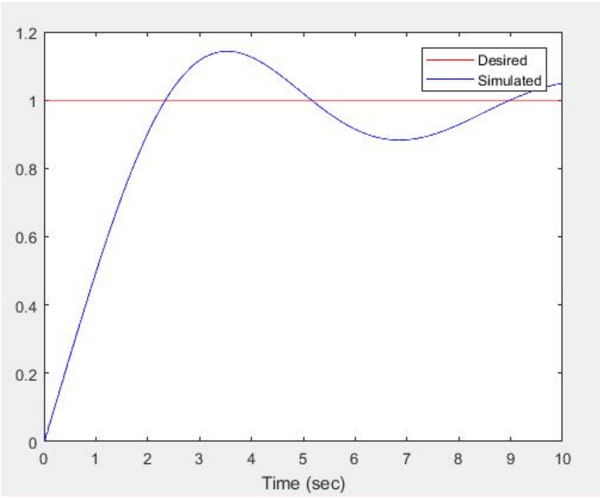
In some other situations, the decision-maker (DM) does not think thecommonly-used probability distribution is always appropriate, especially when the information is vague, relating to human language and behavior, imprecise/ambiguous system data, or when the information could not be described and defined well due to limited knowledge.Such types of uncertainty are categorized as fuzziness which can be further classified into ambiguity or vagueness. Vagueness here is associated with the difficulty of making sharp or precise distinctions.



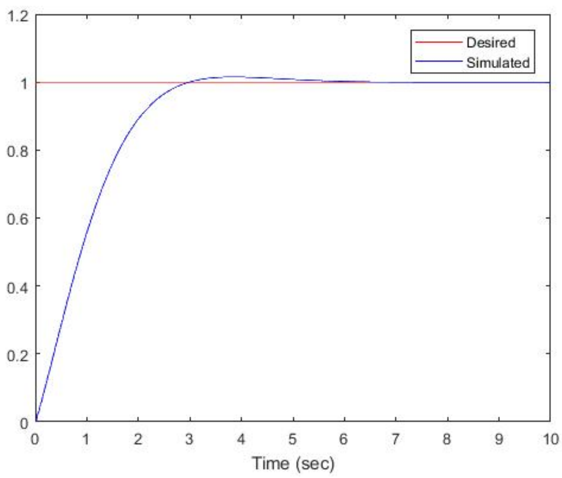


Fig 4.1 Fuzzy Optimization GraphFig 4.2 Nelder Mead Optimization Graph

NELDER MEAD OPTIMIZATION:

In this method used for Multidimensional unconstrained optimization for minimize the function without using derivative for problems with discontinuous function.The output of Nelder Mead Optimization is slightly oscillated.For two variables, a simplex is a triangle, and the method is a pattern search that compares function values at the three vertices of a triangle.The worst vertex, where *f (x, y)* is largest, is rejected and replaced with a new vertex.A new triangle is formed and the search is continued. The process generates a sequence of triangles (which might have different shapes), for which the function values at the vertices get smaller and smaller. The size of the triangles is reduced and the coordinates of the minimum point are found.

Nelder-Mead methodcan become very inefficient for large dimensional problems. This is the so-called effect of dimensionality.Nelder-Mead simplex algorithm possesses a descent property when the objective functionis uniformly convex. This property offers some new insights on why the standardNelder-Mead algorithm becomes inefficient in high dimensions, complementing. The existing explanations given in Torczon and in Han and Neumann.

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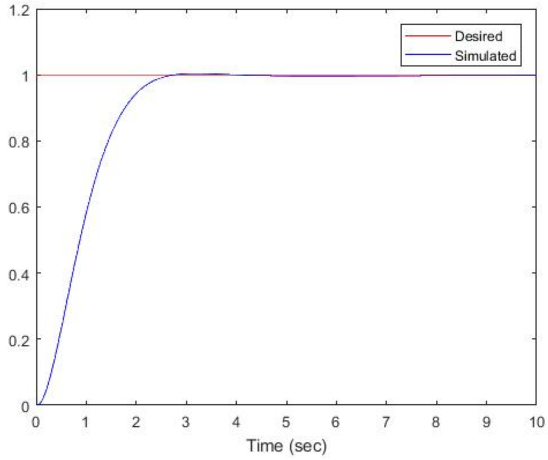
PARTICLE SWARM OPTIMIZATION:

PSO is a computational method.It solves a problem by having population of candidate's solutions here dubbed particles and moving these particles around in the search space.Each particles movement is influenced by its local's best known positions in the search space.The output of PSO is settled on the desired value when compared to other optimization methods, so this optimization is best.The implementation of one paradigm is discussed in more detail, followed by results obtained from applications and tests upon which the paradigm has been shown to perform successfully.

Particle swarm optimization has roots in two main component methodologies. Perhaps more obvious are its ties to artificial life (A-life) in general, and to bird flocking, fish schooling, and swarming theory in particular.It requires only primitivemathematical operators, and is computationally inexpensive in terms of both memory requirements and speed.

Early testing has found the implementation to be effective with several kinds of problems. This projectdiscusses application of the algorithm to the training of artificial neural network weights; Particle swarm optimization has also been demonstrated to perform well on genetic algorithm test functions.



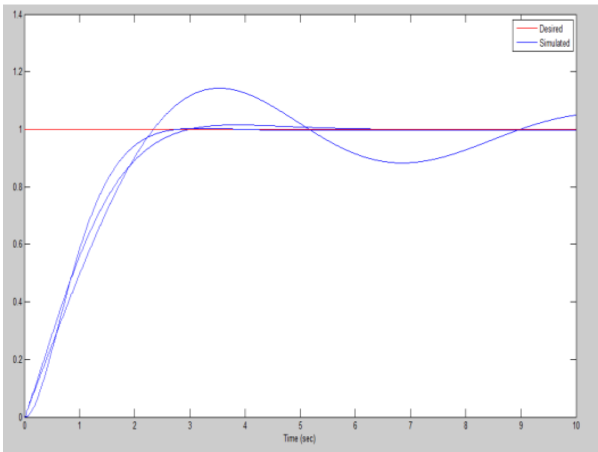


Fig 4.3 PSO Optimization GraphFig 4.4 Overall Output Graph

OVERALL RESULT:

In Particle Swarm Optimization (PSO), the rise time and settling time are decreased and Fuzzy Optimization the settling time is increased when compared to Nelder Mead Optimization. Peak overshoot is not needed for these optimizations. For Fuzzy optimization the input is fuzzification input then the output is defuzzification output. The parameters of characteristics are **Delta, Rise time, Settling time, Peak time**. Desired value means we get minimum value. For Nelder Mead Optimization the oscillation is less when compared to

Fuzzy Optimization. For Fuzzy Optimization the oscillation is high. For Particle Swarm Optimization (PSO) there is no oscillation is occur. The output of PID controller is feedback.

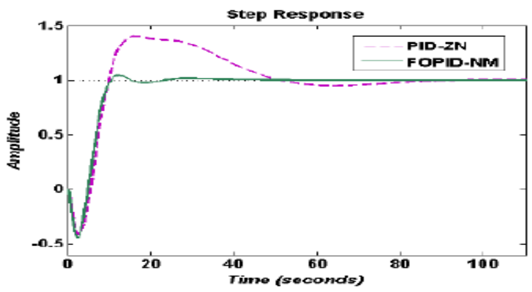


Fig 4.5Comparison of step Response of the NMP system with PID controller and FOPID

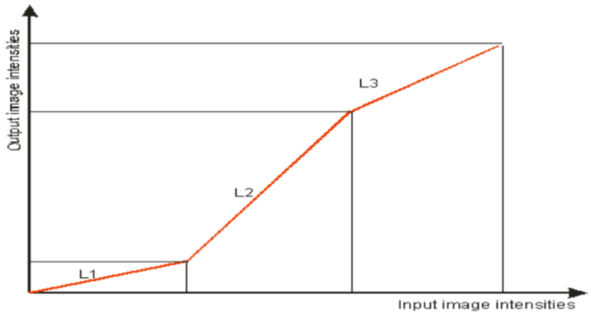


Fig 4.6Output Characteristics of Piecewise Linearizing

CONCLUSION:

In This project we discussed applications of optimization methods for slurry based controller in industrial application. Even though the underlying ideas of optimization are generic and well known, we needed to adapt the methods for the specific industrial context. Such adaptations ranged from being straightforward and easy,to speculative and time consuming to implement.

Table: 5.1 various parameters of different Algorithms

Characteristics	FUZZY Algorithm	PSO Algorithms	Nelder–Mead Algorithm
Rise Time(sec)	0.6583	2.359	0.465
Settling Time(sec)	63.9942	4.1125	35.998
Peak Time(sec)	60.00	40.00	55.00

Therefore, a significant portionof our work focused on prototype implementations to show that the optimizationapproach is feasible. These prototypes also facilitated the experimentation phasein each case study, where we were able to achieve significant and measurableimprovements compared to the state of the practice in the given domain andcontext.The first problem domain that we focused on was maintenance scheduling reducing the total downtime spent on maintenance activities can lead to significantmonetary gains on heavy industrial machinery. Once again, in both casestudies we constructed prototype implementations to demonstrate applicability, and to quantify the performance of our approach on particular industrialsystems.In two different domains, maintenance scheduling and software testing,we showed that the optimization methods can be applied with

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good results,with a varying degree of improvement on the existing systems. A commontheme was that in order to achieve better results that are relevant to the businesslogic of the company, we needed to incorporate enough context dependent information. The prototype implementations that it is indeed feasible to use optimization methods to achieve significant improvements those are applicable to the phenomena of interest.

FUTURE SCOPE:

Work we regarded the maintenance scheduling as a deterministic problem. We primarily use predetermined safe boundaries for maintenance deadlines, which is typical in industrial practice. Whenever new deadlines are available (e.g., as a result of a system inspection by human experts), we calculate new schedules. Another approach would be to consider the maintenance deadlines as probabilistic values from the very start. A major challenge is to get realistic probability distributions, as it would be naive to expect domain experts to come up with probability distributions for each maintenance activity. However, with the rise of data awareness and the urge to collect as much operational data as possible, we are seeing opportunities of accessing huge streams of industrial data, albeit being low-level and unfiltered. On the other hand, probabilistic programming paradigms have emerged and matured to a level that is able to cope with big data. Hence, it would be very interesting to approach the schedulingproblem with a total probabilistic mindset, as a future endeavor.

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