

CHIEF STUDY ON FUZZY COGNITIVE MAPS KNOWLEDGE USING AI

Dr. G. NIRMALA, S. JEEVITHA*

***Principal Kunthavai Naachiyar,
Govt. Arts College (W) Autonomous, Thanjavur, India.**

****Lecturer in Mathematics,
Kunthavai Naachiyar Govt. Arts College (W) Autonomous, Thanjavur, India.**

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ABSTRACT

In this manuscript a new procedure for fuzzy cognitive maps culture is introduced. The projected method is grounded on the reproduction intellect method and it is recycled for the discovery of proper weight matrices that lead the fuzzy cognitive map to wanted stable states. For this purpose a correctly distinct unbiased purpose that incorporates experts' knowledge is constructed and minimized. The submission of the project procedure to a manufacturing regulator problematic supports the claim that the projected method is efficient and robust.

1. INTRODUCTION

Fuzzy cognitive maps (fcms) are a soft computing procedure developed by Kosko as an expansion of cognitive maps which are extensively recycled to signify social scientific knowledge. They belong to the class of neuron-fuzzy systems, which are able to incorporate humanoid knowledge and familiarize it finished culture events. Fcms are designed by experts finished an interactive procedure of knowledge acquisition, and they have a wide field of application, including demonstrating of complex and intelligent schemes, choice examination and extend graph conduct examination. They have also been recycled for planning and decision-making in the fields of international relations and social schemes demonstrating, as well as in management science, operations reexamination and organizational conduct. Dicherson and Kosko have recycled fcms to construct virtual worlds. Furthermore, fcms have been projected for demonstrating supervisory schemes and for decision-making in radiation therapy planning schemes.

The wide recognition of fcms as a talented demonstrating and imitation procedure for complex systems, branded by abstraction, flexibility and fuzzy reasoning, promoted the reexamination on new concepts in this area. However, the established developments still require enhancement, stronger mathematical justification, and further testing on schemes of higher complexity. Moreover, the elimination of deficiencies, such as the abstract estimation of the original weight matrix and the requirement on the subjective cognitive of experts' knowledge, will meaningfully recover fcms' functionality. In this context, the expansion of culture events is a stimulating reexamination topic.

A few events have been projected for fcm culture. The main task of the culture procedure is to find a setting of the fcm's weights that leads the fcm to a wanted stable state. This is achieved finished the minimization of a correctly distinct unbiased function. Established events are deeply reliant on the original weight matrix approximation, which is providing by the experts. Recently, preliminary consequences on a dissimilar approach, grounded on evolution strategies, have been stated.

This manuscript proposes, a new method for fcm learning, which is grounded on the reproduction intellect (AI) method. AI is recycled for the willpower of proper weight matrices for the system, finished the minimization of a correctly distinct unbiased function. AI is designated due to its efficiency and efficiency on a plethora of requests in science and engineering, and its straightforward applicability. The projected method is demonstrated on a manufacturing procedure regulator problem, with talented results.

***Corresponding Author: S. Jeevitha**, **Lecturer in Mathematics,
Kunthavai Naachiyar Govt.Arts College (W) Autonomous, Thanjavur, India.***

The rest of the manuscript is prearranged as follows: in segment 2 the main principles fundamental fcms are described. In segment 3, the AI procedure is fleetingly presented; segment 4 is devoted to the account and examination of the projected culture algorithm. The procedure regulator problem, on which the projected procedure is tested, is labeled in segment 5, though they reached consequences are stated and discussed in segment 6. Segment 7 closes the paper, with conclusions and ideas for future research.

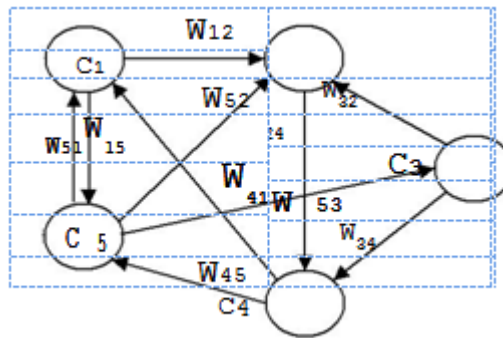


Figure-1: A simple Fuzzy Cognitive Map.

2. OVERVIEW OF FUZZY COGNITIVE MAPS

Fcms have been obtainable by Kosko in 1986 assigned directed graphs for representing causal cognitive and computational inference processing, exploiting a symbolic picture for the account and demonstrating of a system. Concepts are utilized to signify dissimilar aspects of the system, as well as, their behavior. The subtleties of the system are indirect by the communication of concepts. Fcm constructions are recycled to signify both qualitative and quantitative data. The construction of an fcm requires the input of humanoid knowledge and knowledge on the system under consideration. Thus, fcms integrate the accumulated knowledge and knowledge about the fundamental causal relations amongst factors, characteristics, and components that establish the system.

An fcm contains of nodes–concepts, $c_i, i = 1, \dots, n$, where n is the total quantity of concepts. All node–concept, represents one of the key–factors of the system, and it is branded by an assessment $a_i \in [-1, 1], i = 1, \dots, n$. the concepts are interassociated finished biased arcs, which imply the relations amongst them. A simple fcm with five nodes and ten biased arcs is demonstrated in fig. 1. All interconnection amid two concepts c_i and c_j , has a weight w_{ij} , which is proportional to the strength of the causal link amid c_i and c_j . The sign of w_{ij} indicates whether the relation amid the two concepts is direct or inverse. The way of connection indicates whether the notion c_i causes the notion c_j or vice versa. Thus, there are three types of weights:

Humanoid knowledge and knowledge on the system controls the type and the quantity of nodes, as well as the original weights of the fcm. The assessment a_i , of a notion c_i , expresses the quantity of its consistent bodily assessment and is resulting by the alteration of the fuzzy values allocated by the experts, to arithmetical values. Having allocated values to the concepts and the weights, the fcm converges to a stable state, finished the communication procedure then described.

At all step, the assessment a_i of a notion is influenced by the values of concepts–nodes associated to it, and is updated according to the scheme.

Where $\lambda > 0$ is a limit that controls its steepness in the area about zero. In our approach, the assessment $\lambda = 1$ has been used. This purpose is designated since the values a_i of the concepts, by definition, must lie within. The communication of the fcm consequences after a few repetitions in a stable state, i.e. the values of the concepts are not modified further. Wanted values of the production concepts of the fcm guarantee the proper process of the simulated system.

The design of an fcm is a procedure that deeply relies on the input from experts. At the beginning, experts are pooled to control the relevant factors that will be reobtainable in the map as concepts. Then, all expert describes the causal relations amongst the concepts using a linguistic notion. First, experts control the inspiration of a notion on another, as “negative”, “positive” or “no influence”. Then, linguistic weights, such as “strong”, “weak”, etc., are allocated to all arc. The linguistic variables that describe all arc, for all expert, are distinct in. the linguistic variables are combined, and the aggregated linguistic mutable is transformed to a single linguistic weight, finished the sum method. Finally, the center of area (CoA) defuzzification method, is recycled for the alteration of the linguistic weight to an arithmetical assessment within the range. This procedure has the advantage that experts are not required to assign directly arithmetical values to connection relationships, but rather to describe qualitatively the degree of connection amongst the concepts. thus, an original matrix $w^{original} = [w_{ij}], i, j = 1, \dots, n$, with $w_{ii} = 0, i = 1, \dots, n$, is obtained. Using the original notion values, a_i , which are also providing by the experts, the matrix $w^{original}$ is recycled for the willpower of the stable state of the fcm, finished the submission of the rule of eq. (1).

The critical requirement on the sentiments of the experts and the possible meeting to unwanted stable states, are the two most noteworthy weaknesses of fcms. Culture events establish means to increase the efficiency and robustness of fcms, by updating the weight matrix so as to circumvent meeting to unwanted stable states. Up-to-date, there are just a few fcm culture events and they are mostly grounded on ideas coming from the field of reproduction neural networks exercise. Such events start from an original state and an original weight matrix, $w^{initial}$, of the fcm, and familiarize the weights, in order to compute a weight matrix that leads the fcm to a wanted stable state. The wanted stable state is branded by values of the fcm's production concepts accepted by the experts, *ex post*.

The main drawback of this method is the heavy requirement of the final weights on the original weight matrix.

A novel culture procedure that alleviates the problematic of the possible meeting to an unwanted stable state, is projected in this paper. This method is grounded on an intellect procedure which is fleetingly obtainable in the next section.

3. THE PRODUCTION INTELLECT METHOD

Reproduction intellect (ai) is a stochastic optimization algorithm. More specifically, it belongs to the class of *intellect* algorithms, which are inspired from the social subtleties and emergent conduct that arise in socially prearranged colonies.

AI is a populace grounded algorithm, i.e., it exploits a populace of persons to probe talented regions of the examination space. In this context, the populace is called *and* the persons (i.e., the examination points) are called *particles*. All element moves with an adaptable rapidity within the examination space, and retains a memory of the best location it ever encountered. In the *global* irregular of ai, the best location ever reached by all persons of the is associated to all the particles. In the *local* variant, all element is allocated to a topological community consisting of a pre specified quantity of particles. In this case, the best location ever reached by the atoms that comprise the community is associated amongst them.

Assume a d -dimensional examination space, $s \subset \mathbb{R}^d$ and a consisting of n particles. the i -th element is in effect a d -dimensional route $x_i = (x_{i1}, x_{i2}, \dots, x_{id}) \in s$. the rapidity of this element is also a d -dimensional vector, $v_i = (v_{i1}, v_{i2}, \dots, v_{id}) \in s$. the best preceding location met by the i -th element is a point in s , denoted by $p_i = (p_{i1}, p_{i2}, \dots, p_{id}) \in s$. assume g_i to be the index of the element that reached the best preceding location amongst all the atoms in the community of the i -th particle, and t to be the iteration counter. Then, the is manipulated by the equations

where $i = 1, \dots, n$; $c1$ and $c2$ are two strictures called *cognitive* and *social* strictures respectively; r_1, r_2 , are random numbers consistently distributed within ; and g_i is the index of the element that reached either the best location of the whole (global version), or the best location in the community of the i -th element (local version). The strictures χ and w are called *tightening factor* and *inertia weight* respectively, and they are recycled as mechanisms for the regulator of the velocity's magnitude, consistent to the two main ai versions.

The assessment of the tightening factor is resulting analytically. On the other hand, the inertia weight, w , is computed empirically, taking into deliberation that large values encourage global exploration, though small values promote local exploration. According to a rule of thumb, an original assessment of w about 1.0 and a gradual decline in the direction of 0 is measured a proper choice.

In general, the tightening factor form of ai is faster than the one with the inertia weight, though in some requests its global irregular suffers from premature convergence. About the social and cognitive parameter, the default values $c1 = c2 = 2$ have been proposed. the initialization of the and the velocities, is usually achieved arbitrarily and consistently in the examination space, though more sophisticated initialization techniques can enhance the overall presentation of the procedure .

4. THE PROJECTED APPROACH

The present effort focuses on the expansion of an fcm culture procedure grounded on ai. The purpose is to control the values of the cause-effect relations amongst the concepts, i.e. the values of the weights of the fcm that produce a wanted conduct of the system. The willpower of the weights is of major significance and it contributes in the direction of the establishment of fcms as a robust methodology. The wanted conduct of the system is branded by production notion values that lie within wanted constraints pre specified by the experts. These constraints are in over-all problematic dependent.

The culture procedure is, to some extent, similar to that of neural networks training. Let c_1, \dots, c_n , be the concepts of an fcm, and let $c_{out1}, \dots, c_{outm}$, $1 \leq m \leq n$, be the production concepts, though the residual concepts are measured input, or interior, concepts. The user is interested in restricting the values of the production concepts in strict bounds.

Restrung-minded by the experts, which are crucial for the proper process of the demonstrated system. thus, the main goal is to detect a weight matrix, $w = , i, j = 1, \dots, n$, that leads the fcm to a stable state at which, the production concepts lie in their consistent bounds, though the weights retain their bodily meaning. The latter is reached by imposing restraints on the possible values expected by weights. To do this, we consider the subsequent unbiased function $a_{outi}, i = 1, \dots, m$, are the stable state values of the production concepts, that are reached finished the submission of the procedure of eq. (1), using the weight matrix w . obviously, the global minimizers of the unbiased purpose f .

Weight matrices that lead the fcm to a wanted stable state, i.e. all production concepts are bounded within the wanted regions? The unbiased purpose f suits straightforwardly the problem, however, it is non-differentiable and, thus, gradient-grounded methods are not applicable for its minimization. On the other hand, in the projected approach, a_i is recycled for the minimization of the unbiased purpose distinct by eq. (5). The non-differentiability of f poses no problems in our method since a_i , like all evolutionary algorithms, requires purpose values solely, and can be practical even on discontinuous functions. the weight matrix w is retainable by a route which contains of the rows of w in turn, excluding the elements of its main diagonal, $w_{11}, w_{22}, \dots, w_{nn}$, which are by meaning equal to zero.

Thus, an fcm with n fully interassociated concepts (i.e. all notion interacts with all other concepts), agrees to an $n(n - 1)$ -dimensional minimization problem. If some interconnections are missing, then their consistent weights are zero and they can be omitted, reducing the dimensionality of the problem. This is most often the case, since the fcms providing by experts are rarely fully connected.

All interconnection of an fcm has a precise bodily meaning, and, thus, several restraints are posed by the experts on the values of the weights. Restraints are providing in the form of undesirable or positive relations amid two concepts. So, if two concepts c_i and c_j are negatively related, then the weight $w_{ij} \in$, though if they are positively related, it takes values within. more strict restraints may be additionally posed on some weights, either by the experts, or by taking into deliberation the convergence

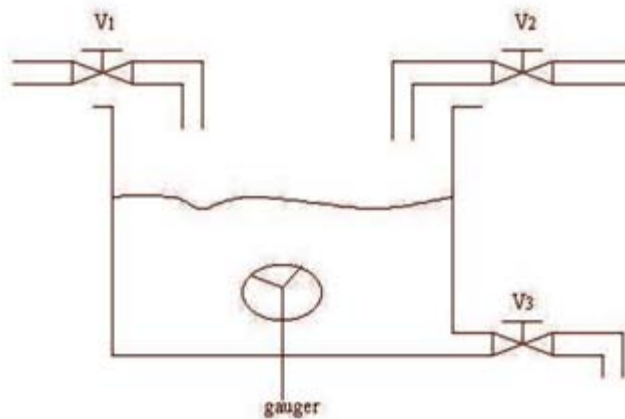


Figure-2: illustration of a procedure regulator problematic from industry.

Regions reached finished the submission of the culture algorithm, as demonstrated in segment 6. Such restraints may enhance the overall presentation of the algorithm.

The submission of a_i for the minimization of the unbiased purpose f , starts with an initialization phase, where a swarm, $s = \{x_1, \dots, x_m\}$, of size m , is generated randomly, and it is evaluated using f . then, the eqs. are recycled to evolve the swarm. As soon as a weight configuration that globally minimizes f is reached, the procedure is terminated. A flowchart of this procedure is portrayed in fig. 2.

There is, in general, a plethora of weight matrices that lead to meeting of the fcm to the wanted regions of the production concepts. a_i is a stochastic algorithm, and, thus, it is quite natural to obtain such sub optimal matrices which differ in subsequent experiments. all these matrices are proper for the design of the fcm and follow the restraints of the problem, though, all matrix may have dissimilar bodily connotation for the system. Statistical examination of the reached weight matrices may help in the better understanding of the system's dynamic, as it is indirect by the weights, as well as in the selection of the most suitable suboptimal matrix. Any material available *a priori*, may be incorporated to enhance the procedure, either by modifying the unbiased purpose in order to exploit the available information, or by imposing further restraints on the weights. The projected method has proved to be very efficient in practice. In the subsequent section, its process on a manufacturing procedure regulator problem, is illustrated.

5. AN MANUFACTURING PROCEDURE REGULATOR PROBLEM

A simple procedure regulator problematic met in biochemical industry, is designated to illustrate the workings of the projected culture procedure. The procedure regulator problem, demonstrated in fig. 3, contains of one tank and three valves that inspiration the quantity of a liquid in the tank. Valve1 and valve 2 pour two dissimilar liquids into the tank. Duringthe mixing of the two liquids, a biochemical reaction takes place in the tank, and a new liquid is produced. Valve3 empties the tank when the new liquid shaped reaches a precise level. A sensor is placed inside the tank to measure The precise gravity of the shaped liquid. When the value, g , of the precise gravity lies in a range, the wanted liquid has been produced. There is also a limit on the height, t , of the liquid in the tank, i.e. it cannot exceed a lower limit t_{\min} and an upper limit t_{\max} . The regulator target is to keep the two variables, t and g , within their bounds:

Agroup of experts constructs the fcm for the imitation of this system, subsequent the procedure labeled in segment 2. The fcm that models and controls the precise system is portrayed in fig. 4. It contains of five concepts which are distinct as:

- Notion 1 – the quantity of the liquid in the tank. it depends on the operational state of valves 1, 2 and 3;
- Notion 2 – the state of valve 1 (closed, open or partly opened);
- Notion 3 – the state of valve 2 (closed, open or partly opened);
- Notion 4 – the state of valve 3 (closed, open or partly opened);
- Notion 5 – the precise gravity of the shaped liquid in the tank.

Thereis a consensus amongst the experts about the way of the arcs amongst the concepts. For all weight, the overall linguistic mutable and its consistent fuzzy set, are also strong-minded by the experts. Theranges of the weights indirect by the fuzzy regions, are:

Andthe original weight matrix, resulting finished the CoA defuzzification method, is:

Allexperts decided on the same range for the weights w_{21} , w_{31} , and w_{41} , and most of them decided on the same range for the weights w_{12} and w_{13} . However, there was no such agreement on the cases of the weights w_{15} , w_{52} , and w_{54} , where their sentiments varied significantly.

Aiis practical to update the eight nonzero weight values of the fcm. To circumvent physically empty weights, the constraints or,indirect by the directions of the consistent arcs of the fcm, are compulsory on all weight.

Theproduction concepts for this problematic are the concepts c_1 and c_5 . Thewanted regions for the two production concepts, which are crucial for the proper process of the demonstrated system, have been distinct by the experts:

Inthe next section, the simulation consequences are stated and analyzed.

6. SIMULATION RESULTS

The conduct of the system accepting all the weights' restraints compulsory by the experts has been investigated. Thereached consequences are very interesting and deliver insight about the appropriateness of the experts' proposals as well as suboptimal weight matrices that lead the fcm to the wanted stable state.

A total of 100 in reliant on trials have been achieved using the local irregular of the tightening factor ai version, with community size equal to 3. This form was designated due to its fast meeting rates and efficiency. Size has been set equal to 20 for all experiments, since it proved sufficient to detect global minimizers of the unbiased purpose professionally and efficiently. Moreover, further trials with larger swarms and dissimilar ai forms did not result in meaningfully dissimilar meeting rates, in footings of the required quantity of purpose evaluations. The tightening factor as well as the cognitive and the social strictures have been set to their optimal values, $\chi = 0.729$, $c_1 = c_2 = 2.05$. The accuracy for the willpower of the global minimizer of the unbiased function, has been equal to 10^{-8} .

	W12	W13	W15	W21	W31	W41	W52	W54
Mean	-0.4027	-0.2016	0.8991	0.3999	0.5000	-0.8000	0.9659	0.1043
Median	-0.4329	-0.2000	0.9050	0.4000	0.5000	-0.8000	0.9837	0.1000
St.Dev.	0.0487	0.0056	0.0909	0.0011	0.0003	0.0002	0.0420	0.0090
Min	-0.4500	-0.2291	0.7156	0.3889	0.4971	-0.8014	0.8685	0.1000
Max	-0.3500	-0.2000	1.0000	0.4000	0.5000	-0.8000	1.0000	0.1363

About the weights, the restraints distinct by eqs., which are resulting by the fuzzy regions projected by the experts, have been initially used. however, no solution was detected, indicating that the optional ranges for the weights, as well as the original weight matrix, w^{initial} , providing by the experts are not proper and do not lead the fcm to the wanted stable state. the best weight matrix noticed in these regions, in footings of its unbiased purpose assessment (i.e. the matrix that agrees to the smallest unbiased purpose value) .

Since the deliberation of all eight restraints on the weights prohibits the discovery of a suboptimal matrix, some of the restraints were omitted. Specifically, the restraints for the three weights w_{15} , w_{52} , and w_{54} , for which the experts' proposals about their values varied widely, were omitted, one by one at the beginning, and then in pairs. The consistent weights were allowed to assume values in the range or, in order to circumvent physically empty weight matrices. Despite this, no solutions were noticed in these cases. However, suboptimal matrices were noticed after omitting all three constraints. The statistics of the weights' values for this case are stated in table 1 and portrayed in the boxplot of fig. 2. As shown in the figure, the weights w_{21} , w_{31} , and w_{41} , congregated to nearly the same assessment in all experiment; an assessment which is close to the constraints distinct by the experts. The weights w_{13} and w_{54} congregated also in very small ranges, though the residual weights expected values in wider regions. Moreover, the three unconstrained weights w_{15} , w_{52} , and w_{54} , congregated in regions meaningfully dissimilar than those strong-minded by the experts. The mean quantity of AI repetitions required in the trials was 40.

The ranges of the production concepts' values for the reached suboptimal matrices are portrayed in fig. 6. The production notion $c1$ converges to nearly the same assessment for all suboptimal matrix, though $c5$ takes a wide range of values, always within the wanted bounds. About the residual concepts, c_3 and c_4 , they converge to nearly the same values, though the values of $c2$ vary slightly. The obtained

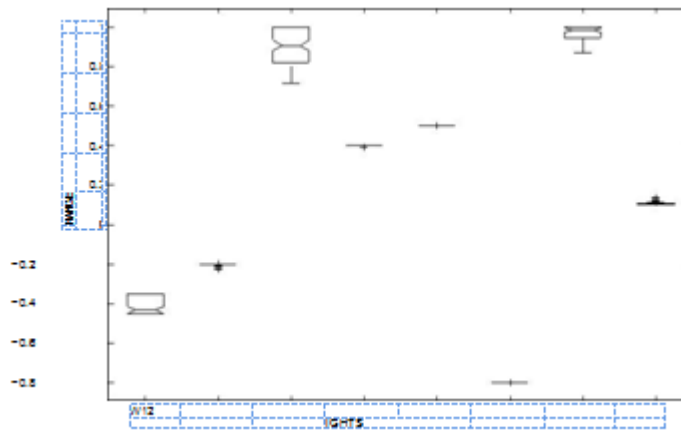


Figure 3: Boxplot of the obtained results for the weights for the first scenario.

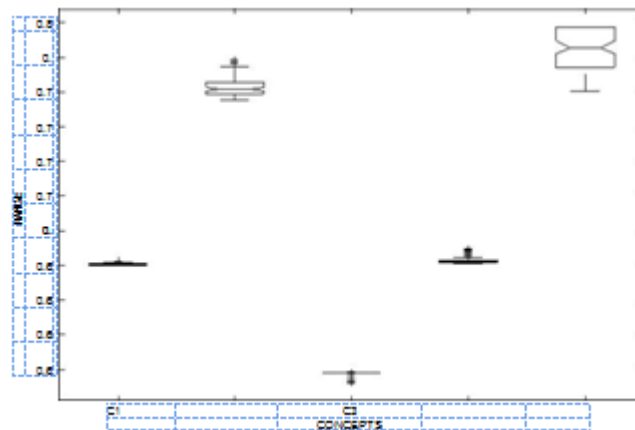


Figure 4: Boxplot of the obtained results for the concepts for the first scenario.

Values for these three concepts are physically meaningful and suitable for the process of the system.

One of the reached suboptimal matrices is the following:

It is clear from the reached consequences that there is a noteworthy divergence of some weights from the original weight values optional by the experts. The weights w_{21} , w_{31} , and w_{41} , take nearly identical values in every experiment, near the original constraints optional by the experts. Finally, the weight w_{12} deviates somewhat from its original region. Thus, the projected culture procedure is able to deliver proper weight matrices for the design of the fcm, professionally and effectively, alleviating shortages care cycled by deviation in the experts' suggestions. Exploiting a priori information, such as restraints posed by the experts on weights, enhances its performance. Moreover, a primitive statistical study of the reached consequences delivers an intuition on the process and the subtleties of the demonstrated system.

7. CONCLUSIONS

Fuzzy cognitive maps (fcms) are extensively recycled to successfully model and analyze complex systems. The need to recover the functional picture of fcms has been outlined. A new culture procedure for determining suboptimal weight matrices for fuzzy cognitive maps with fixed structures, in order to rally a wanted stable state, is introduced. The projected method is grounded on the minimization of a correctly distinct unbiased purpose finished the reproduction intellect algorithm. The new culture method for the willpower of the fcm's weight matrix is formulated and explained.

A manufacturing procedure regulator problematic is recycled for the illustration of the projected culture algorithm. The consequences appear to be very promising, verifying the efficiency of the culture procedure. The bodily connotation of the reached consequences is retained. The projected method also delivers a robust solution in the event of divergent sentiments of the experts about the system.

8. FUTURE ENHANCEMENT

Future effort will consider further investigation of the projected method considering dissimilar scenarios of the employed manufacturing problematic as well as requests on schemes of higher complexity.

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