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EVOLUTIONARY ARTIFICIAL NEURAL NETWORK FOR SELECTING FLEXIBLE MANUFACTURING SYSTEMS UNDER DISPARATE LEVEL-OF-SATISFACTION OF DECISION MAKER

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Abstract. *This paper proposes the application of Meta-Learning Evolutionary Artificial Neural Network (MLEANN) in selecting the best flexible manufacturing systems (FMS) from a group of candidate FMSs. Multi-criteria decision-making (MCDM) methodology using an improved S-shaped membership function has been developed for finding out the "best candidate FMS alternative" from a set of candidate-FMSs. The MCDM model trade-offs among various parameters, viz., design parameters, economic considerations, etc., affecting the FMS selection process under multiple, conflicting-in-nature criteria environment. The selection of FMS is made according to the error output of the results found from the proposed MCDM model.*
Keywords: Neural networks, Meta-learning, Flexible manufacturing systems, Hybrid approach, Multi criteria decision-making,

1. Introduction.

Flexible manufacturing system (FMS) is a set of integrated computer controlled automated material handling equipments and numerical controlled machine tools capable of processing a variety of machine parts. FMSs are popular in industries [10, 11, 15] due to its competitive advantages, e.g., flexibility, speed of response, quality, reduced lead-time, reduced labour etc. Manufacturing strategy is purely a choice of alternatives aiming towards better productivity as well as profit thereby maintaining quality of product and responsiveness to customers. In this rapid liberalised economic scenario, the overall objective is to purchase a minimum amount of capacity (i.e., capital investment) and utilize it in the most effective way. Though FMS is an outgrowth of existing manufacturing technologies, its selection is not fully studied. It has been a focal point in manufacturing related research since early 1970s. FMS provides a low inventory environment with unbalanced operations unique to the conventional production environment. Process design of FMS consists of a set of crucial decisions that are to be made carefully. It requires decision-making, e.g., selection of CNC machine tool, material handling system, product mix, etc. Thus, the selection of FMS requires trading-off among the various parameters of the FMS alternatives. The selection parameters are conflicting in nature. High quality management is not enough for dealing with the complex and ill-structured factors that are conflicting-in-nature [4]. Therefore, there is a need for sophisticated and applicable technique to help the decision-makers for selecting the proper FMS in a manufacturing organization [12, 14, 16, 20]. AHP [17] (analytic hierarchy process) has been widely used for tackling FMS selection problems due to the concept's simplicity and efficiency [9]. Researchers [1, 3, 13] use the AHP technique for the evaluation of engineering problems.

Most of the work reported in the field of multiple criteria decision-making (MCDM) application to select best possible FMS alternative from a group of candidate-FMSs contain data with hidden errors. Thus, an attempt has been made in this paper using Meta-Learning Evolutionary Artificial Neural Network (MLEANN) [2] approach to select the best possible FMS from a group of candidate-FMS's. The selection is made by trading off the errors of output data while using the fuzzy-MCDM approach based on AHP.

2. **Evolutionary Artificial Neural Network (EANN).** A Meta-Learning Evolutionary Artificial Neural Network (MLEANN) framework is proposed in this paper where evolution can be introduced at various levels [2]. At the lowest level, the evolution can be introduced into weight training, where ANN weights are evolved. At the next higher level, the evolution can be introduced into neural network architecture adaptation, where the architecture (number of hidden layers, no of hidden neurons and node transfer functions) is evolved. At the highest level, the evolution can be introduced into the learning mechanism. A general framework of MLEANN which includes the above three levels of evolution is given in Figure 1. From the point of view of engineering, the decision on the level of evolution depends on what kind of prior knowledge is available [2]. The efficiency of evolutionary training can be improved significantly by incorporating a local search procedure into the evolution. In this research, back-propagation (BP) algorithm is used as the local search algorithm. All the randomly generated architectures of the initial population are trained by BP algorithm for a fixed number of epochs. The learning rate and momentum of the BP algorithm are adapted according to the problem concerned. The basic algorithm of the MLEANN framework is given below:

1. Set $t = 0$ and randomly generate an initial population of neural networks with architectures, node transfer functions and connection weights assigned at random.
2. Evaluate fitness of each ANN using BP algorithm
3. Based on fitness value, select parents for reproduction
4. Apply mutation to the parents and produce offspring (s) for next generation. Refill the population back to the defined size.
5. Repeat step 2

6. *Stop* when the required solution is found or number of iterations has reached the required limit.

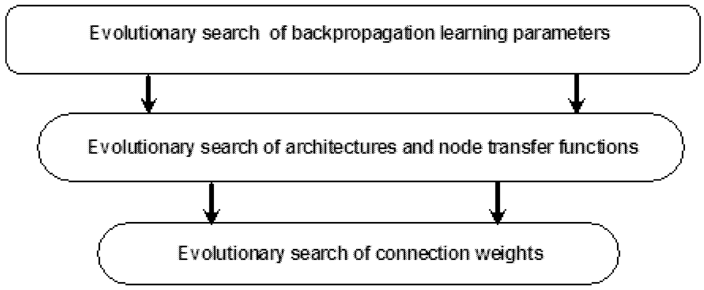

FIGURE 1. Interaction of various evolutionary search mechanisms

All the randomly generated architecture of the initial population is trained by the back-propagation (BP) algorithm.

2.1. **Genetic programming.** MLEANN performance is compared with two Genetic Programming (GP) models to learn the different decision regions. Linear Genetic Programming (LGP) and Multi Expression Programming (MEP) are explored in this paper.

2.1.1. *Linear genetic programming (LGP).* Linear genetic programming is a variant of the GP technique that acts on linear genomes [4]. Its main characteristics in comparison to tree-based GP lies in that the evolvable units are not the expressions of a functional programming language (like LISP), but the programs of an imperative language (like C/C++).

2.1.2. *Multi expression programming (MEP).* MEP genes are sub-strings of a variable length [13]. The number of genes per chromosome is constant. This number defines the length of the chromosome. Each gene encodes a terminal or a function symbol. A gene that encodes a function includes pointers towards the function arguments.

3. **FMS Selection Problem.** The nomenclature used in the MCDM model for FMS selection problem is given below:

D: Decision matrix; A: Pair-wise comparison matrix among criteria (m x n); m: Number of criteria; n: Finite number of candidate-alternatives of the pair-wise comparison matrix; $\eta_{\max}$: Principal eigen-value of 'A' matrix; PV: Priority Vector; α : Objective factor decision weight , i.e., level of satisfaction of DM; OFM: Objective Factor Measure; SFM: Subjective Factor Measure; OFC: Objective Factor Cost; I.I.: Inconsistency Index of 'A' matrix; R.I.: Random inconsistency Index of 'A' matrix; I.R.: Inconsistency Ratio of 'A' matrix; SI: Selection Index and β : Fuzzy parameter which measures the degree of vagueness, $\beta = 0$ indicates crisp.

The MCDM model [5, 8] considers cardinal and ordinal preferences under disparate level-of-satisfaction of the decision maker (DM). AHP provides the DM's with a vector of priorities (PV) to estimate the expected utilities of each candidate-FMS. A mathematical model is proposed by Bhattacharya *et al.* [7, 8] to combine cost factor components with the importance weightings found from AHP. The governing equation of the said model is:

$$SI_i = [(\alpha \times SFM_i) + (1 - \alpha) \times OFM_i] \tag{1}$$

where,

$$OFM_i = \frac{1}{[OFC_i \times \sum_{i=1}^{n} OFC^{-1}]} \tag{2}$$

In the above mentioned model, AHP plays a crucial role. AHP is an MCDM method and it refers to making decisions in the presence of multiple, usually conflicting, criteria. A criterion is a measure of effectiveness. It is the basis for evaluation. Criteria emerge as a form of attributes or objectives in the actual problem setting. In reality, multiple criteria usually conflicts each other having incommensurable units of measurement.

As a first step in testing the MCDM model proposed, the authors illustrate an example with FMS selection. Six different types of objective cost components are identified for the selection problem. The total costs of each alternative are nothing but the Objective Factor Costs (OFC's) of the FMS's (refer to Table 1). The task is to select the best candidate-FMS among five candidate-FMS's. Table 1 breaks down the costs of the five FMS candidate-alternatives in order to calculate OFC and OFM values.

Table 1. Cost factor components (in US\$ $\times 10^5$)

	FMS				
OFCs	FMS_1	FMS_2	FMS_3	FMS_4	FMS_5
1. Cost of Acquisition	1.500	0.800	1.300	1.000	0.900
2. Cost of Installation	0.075	0.061	0.063	0.053	0.067
3. Cost of Commissioning	0.063	0.052	0.055	0.050	0.061
4. Cost of Training	0.041	0.043	0.046	0.042	0.040
5. Cost of Operation	0.500	0.405	0.420	0.470	0.430
6. Cost of Maintenance	0.060	0.070	0.065	0.054	0.052
Total Cost (OFC)	2.239	1.431	1.949	1.669	1.550
Objective Factor Measure (OFM_i)	0.154	0.241	0.177	0.206	0.222

The subjective attributes influencing the selection of FMS are shown in Table 2. Table 2 consists of five different attributes, viz., flexibility in pick-up and delivery, flexibility in conveying system, flexibility in automated storage and retrieval system, life expectancy / pay back period and tool magazine changing time. One may consider other attributes appropriate to selection of FMS.

Table 2. Attributes influencing the FMS selection problem

Factor I	Factor II	Factor III	Factor IV	Factor V
Flexibility in pick-up and delivery	Flexibility in conveying system	Flexibility in automated storage and retrieval system	Life expectancy / pay back period	Tool magazine changing time

A decision matrix is constructed by assigning weights to each of the factors based on the relative importance of its contribution according to a nine-point scale (Table 3). Assigning the weights to each of the candidate-alternatives for each factor follows the same logic as that of the decision matrix. This matrix is known as pair-wise comparison matrix. The PV values are determined then for both the decision and pair-wise comparison matrices. The $\eta_{\max}$ for each matrix may be found by multiplication of sum of each column with the corresponding PV value and subsequent summation of these products.

TABLE 3. The nine-point scale of pair-wise comparison.

Intensity scale	Interpretation
1	Equally important
3	Moderately preferred
5	Essentially preferred
7	Very strongly preferred
9	Extremely preferred
2, 4, 6, 8	Intermediate importance between two adjacent judgments

For assigning the weights to each of the attributes as well as to the alternative processes for constructing the decision matrix and pair-wise comparison matrices, the phrases like "much more important" is used to extract the decision maker's preferences. Saaty [17] gave an intensity scale of importance (Table 3) and has broken down the importance ranks.

In this paper, the proposed methodology is applied to calculate the priority weights for functional, design factors and other important attributes by Eigen vector method for each pair-wise comparison matrices. Next, global priorities of various attributes rating are found by using AHP. These global priority values are used as the subjective factor measures (SFM) in equation (1). The pair-wise comparison matrices for five factors of the FMS selection problem are constructed on the basis of Saaty's nine-point scale (Table 3). The objective factors, i.e., objective factors measures (OFM) and objective factor components (OFC) are calculated separately by using cost factor components.

There is a "check" in the judgmental values given to the decision and pair-wise comparison matrices for revising and improving the judgments. If I.R. is greater than 10%, the values assigned to each element of the decision and pair-wise comparison matrices are said to be inconsistent. For I.R. < 10%, the level of inconsistency is acceptable. Otherwise the level of inconsistency in the matrices is high and the decision-maker is advised to revise the judgmental values of the matrices to produce more consistent matrices. It is expected that all the comparison matrices should be consistent. But the very root of the judgment in constructing these matrices is the human being. So, some degree of inconsistency of the judgments of these matrices is fixed at 10%.

Calculation of I.R. involves I.I., R.I. and I.R. These are evaluated from equations (5), (6) and (7) respectively.

$$\text{I.I.} = \frac{(\eta_{\max} \text{ - } n)}{(n \text{ - } 1)} \quad \ldots \tag{3}$$

$$\text{R.I.} = \frac{[1.98 \text{ x } (n \text{ - } 2)]}{n} \ldots \tag{4}$$

$$\text{I.R.} = \frac{\text{I.I.}}{\text{R.I.}} \ldots \tag{5}$$

The SFM_i values are the global priorities for each candidate-alternative. SFM_i values are found by multiplying each of the decision matrix PV value to each of the PV value of each candidate-alternative for each factor. Each product is then summed up for each alternative to get SFM_i.

A set of seven matrices is constructed based upon the importance weightages (Table 3). A_1 is the decision matrix based on the judgemental values from different judges. Matrices D, $A_2 - A_4$ show comparisons of the weightages for each of the attribute. Matrix G consolidates the results of the earlier tables in arriving at the composite weights, i.e., SFM_i values, of each of the alternatives.

$$A_1 = \begin{bmatrix} 1 & 3 & 2 & 5 & 4 \\ \frac{1}{3} & 1 & \frac{1}{3} & 5 & 2 \\ \frac{1}{2} & 3 & 1 & 4 & 3 \\ \frac{1}{5} & \frac{1}{5} & \frac{1}{4} & 1 & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{2} & \frac{1}{3} & 3 & 1 \end{bmatrix} \qquad D = \begin{bmatrix} 1 & 5 & 3 & 4 & 5 \\ \frac{1}{5} & 1 & \frac{1}{3} & \frac{1}{2} & 1 \\ \frac{1}{3} & 3 & 1 & 3 & 5 \\ \frac{1}{4} & 2 & \frac{1}{3} & 1 & 3 \\ \frac{1}{5} & 1 & \frac{1}{5} & \frac{1}{3} & 1 \end{bmatrix}$$

A_1: Decision matrix; D: Pair-wise comparison matrix for 'Factor I'.

$$A_2 = \begin{bmatrix} 1 & 7 & 3 & 5 & 6 \\ \frac{1}{7} & 1 & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} \\ \frac{1}{3} & 4 & 1 & 3 & 4 \\ \frac{1}{5} & 3 & \frac{1}{3} & 1 & 2 \\ \frac{1}{6} & 2 & \frac{1}{4} & \frac{1}{2} & 1 \end{bmatrix} \qquad A_3 = \begin{bmatrix} 1 & 4 & 1 & 3 & 7 \\ \frac{1}{4} & 1 & \frac{1}{4} & \frac{1}{2} & 5 \\ 1 & 4 & 1 & 2 & 7 \\ \frac{1}{3} & 2 & \frac{1}{2} & 1 & 3 \\ \frac{1}{7} & \frac{1}{5} & \frac{1}{7} & \frac{1}{3} & 1 \end{bmatrix}$$

A_2: Pair-wise comparison matrix for 'Factor II'; A_3: Pair-wise comparison matrix for 'Factor III'.

$$A_5 = \begin{bmatrix} 1 & \frac{1}{3} & 5 & 7 & 4 \\ 3 & 1 & 5 & 6 & 4 \\ \frac{1}{5} & \frac{1}{5} & 1 & 2 & \frac{1}{2} \\ \frac{1}{7} & \frac{1}{6} & \frac{1}{2} & 1 & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{4} & 2 & 3 & 1 \end{bmatrix} \qquad A_4 = \begin{bmatrix} 1 & \frac{1}{3} & 5 & 3 & 6 \\ 3 & 1 & 5 & 7 & 6 \\ \frac{1}{5} & \frac{1}{5} & 1 & 2 & 3 \\ \frac{1}{3} & \frac{1}{7} & \frac{1}{2} & 1 & 2 \\ \frac{1}{6} & \frac{1}{6} & \frac{1}{3} & \frac{1}{2} & 1 \end{bmatrix}$$

A_4: Pair-wise comparison matrix for 'Factor IV'; A_5: Pair-wise comparison matrix for 'Factor V'.

$$G = \begin{bmatrix} 0.471 & 0.076 & 0.259 & 0.131 & 0.063 \\ 0.408 & 0.512 & 0.366 & 0.273 & 0.305 \\ 0.159 & 0.051 & 0.104 & 0.501 & 0.458 \\ 0.279 & 0.246 & 0.338 & 0.103 & 0.074 \\ 0.050 & 0.117 & 0.151 & 0.075 & 0.047 \\ 0.103 & 0.075 & 0.040 & 0.047 & 0.116 \end{bmatrix}$$

G: Final matrix to find out global priority.

In the proposed methodology, the unit of OFC (Table 1) is US$, whereas OFM (Table 1) is a non-dimensional quantity. Correspondingly, *SI* is also a non-dimensional quantity. The higher the *SI* values, the better would be the selection. The value of objective factor decision weight (α) lies between 0 and 1. For $\alpha = 0$, $SI =$ SFM, i.e., selection is solely dependent on subjective factor measure values found from AHP and SFM values dominate over OFM values. There is no significance of considering the cost factor components for $\alpha = 0$. For α=1, $SI =$ OFM, i.e., OFM values dominate over the SFM values and the FMS selection is dependent on OFM values only. For α =1, the cost factors get priority than the other factors. Keeping this in mind, the values of α is taken in between 0 and 1 [8].

Equation (6) is the fuzzified equation governing the selection process and it uses a flexible *S*-curve membership function (MF) depicted by equation (7) [5]. For an easy demonstration of the proposed fuzzified MCDM model, efforts for fuzzification are confined assuming that differences in judgemental values are only 5%. One may fuzzify the SFM_i values from the very beginning of the model introducing the modified *S*-curve MF in AHP and the corresponding fuzzification of SI_i indices may also be carried out using the holistic approach used in equation (1). Finally the set of candidate-alternatives may then be ranked according to the descending order of SI_i indices.

$$\tilde{SI_i}\Big|_{\alpha=\alpha_{SFM_i}} = SI_L + \left(\frac{SI_U - SI_L}{\beta}\right) \ln \frac{1}{C}\left(\frac{A}{\alpha_{SI_i}} - 1\right) \tag{6}$$

where SI_U = upper bound of *SI*, and SI_L = lower bound of *SI*; A, B, C are constants.

$$\mu(x) = \begin{cases} 1, & x < x^a; \\ 0.999, & x = x^a; \\ \frac{B}{1+Ce^{\beta x}}, & x^a < x < x^b; \\ 0.001, & x = x^b; \\ 0, & x > x^b. \end{cases} \tag{7}$$

To fit the logistic function into the MCDM model in order to sense its degree of fuzziness the equation (7) is defined as $0.001 \le \mu(x) \le 0.999$. This range is selected because in real-world situation the work force does not need always to be 100% of the requirement. At the same time the work force will not be 0%. Therefore, a range between x^a and x^b with $0.001 \le \mu(x) \le 0.999$ should be fixed for the *S*-curve MF to apply in real-world situations. This concept of the range for $\mu(x)$ is used in this paper.

Computation of the fuzzified MCDM model reveals that amongst all the FMS's, FMS_1 has the highest *SI* value when objective factor decision weight lies between 0.33 and 1.00. However, FMS_2 would be preferred to other FMS candidate-alternatives when the value of level of satisfaction lies between 0.00 and 0.33.

The appropriate value of the level of satisfaction α is to be selected cautiously. The reason behind this is as following. The higher the α value, the dominance of the SFM_i values will be higher. The lower the α value, the more the dominance of cost factor components and subsequently, and the intangible factors will get less priority.

Final selection of the best candidate-FMS alternative is based on the error output of the results found from this MCDM model. The MCDM model is not described in detail herein. Readers may refer to Bhattacharya, Abraham, and Vasant [6] for detailed description of the model and its analysis. The output data of MCDM is treated as input to the experimentation with MLEANN model. Next section describes the procedure as well as results of experimenting with the MLEANN method.

4. **Experimental Results.** We apply the MLEANN framework for evaluating the candidate FMS alternatives. For performance comparison, we use the same set of training and test data that are used for experimentations with conventional design of neural networks. For performance evaluation, the parameters used in our experiments are set to be the same for all the problems. Fitness value is calculated based on the RMSE achieved on the test set. In this research, we have considered the best-evolved neural network as the best individual of the last generation. All the genotypes were represented using binary coding and the initial populations were randomly generated based on the parameters shown in Table 4. LGP used a population size of 100, mutation 50RMSE, and Correlation Coefficient – CC). The use of the three methods and a direct back-propagation approach are illustrated in Table 6. We have illustrated only one performance comparison for $\alpha = 0.1$. Other performance comparisons follow the same procedure. Fitness value is calculated based on the RMSE achieved on the test set. In Table 6 MLEANN has been compared with ANN, MEP and LGP results in regard to RMSE and CC values for each of the five candidate-alternative FMSs. From Table 6, decision maker will be able to select his/her choice depending upon DM's level-of-satisfaction, α, value.

TABLE 4. Parameters used for evolutionary design of artificial neural networks.

Population size	30
Maximum no of generations	25
Number of hidden nodes	5-9 hidden nodes
Activation functions	tanh (T), logistic (L), sigmoidal (S), tanh-sigmoidal ($T*$), log-sigmoidal ($L*$)
Output neuron	linear
Training epochs	500
Initialization of weights	+/- 0.1
Ranked based selection	0.50
Learning rate	0.15-0.01
Momentum	0.15-0.01
Elitism	5 %
Initial mutation rate	0.70

TABLE 5. Candidate-FMSs' ranking.

Candidate-FMS	SI_i values	Rank #
FMS_1	0.249	1
FMS_2	0.224	2
FMS_3	0.210	3
FMS_4	0.155	5
FMS_5	0.162	4

TABLE 6. RMSE and CC values for the different FMS using four different algorithms.

	FMS_1	FMS_2	FMS_3	FMS_4	FMS_5
MLEANN					
RMSE ($\alpha = 0.1$)	0.0082	0.0065	0.0067	0.0084	0.0045
RMSE ($\alpha = 0.5$)	0.0065	0.0075	0.0056	0.0054	0.0063
RMSE ($\alpha = 0.9$)	0.0056	0.0087	0.0067	0.0056	0.0056
CC ($\alpha = 0.1$)	0.999	0.998	0.999	0.998	0.999
CC ($\alpha = 0.5$)	0.999	0.999	0.998	0.999	0.998
CC ($\alpha = 0.9$)	0.998	0.999	0.998	0.998	0.999
ANN					
RMSE ($\alpha = 0.1$)	0.022	0.0365	0.0267	0.0284	0.0245
RMSE ($\alpha = 0.5$)	0.0265	0.0275	0.0256	0.0254	0.0263
RMSE ($\alpha = 0.9$)	0.0256	0.0287	0.0267	0.0256	0.0256
CC ($\alpha = 0.1$)	0.997	0.996	0.997	0.998	0.996
CC ($\alpha = 0.5$)	0.997	0.996	0.997	0.998	0.998
CC ($\alpha = 0.9$)	0.998	0.997	0.996	0.999	0.996
MEP					
RMSE ($\alpha = 0.1$)	0.0263	0.0196	0.0201	0.0154	0.0175
RMSE ($\alpha = 0.5$)	0.0168	0.0199	0.0223	0.0185	0.019
RMSE ($\alpha = 0.9$)	0.0236	0.0287	0.0176	0.0164	0.0177
CC ($\alpha = 0.1$)	0.998	0.998	0.998	0.997	0.999
CC ($\alpha = 0.5$)	0.996	0.998	0.999	0.998	0.998
CC ($\alpha = 0.9$)	0.997	0.997	0.998	0.999	0.998
LGP					
RMSE ($\alpha = 0.1$)	0.1820	0.1965	0.1767	0.1840	0.1745
RMSE ($\alpha = 0.5$)	0.0987	0.0295	0.0324	0.0354	0.02863
RMSE ($\alpha = 0.9$)	0.0216	0.0248	0.0257	0.0216	0.0246
CC ($\alpha = 0.1$)	0.998	0.995	0.996	0.996	0.998
CC ($\alpha = 0.5$)	0.996	0.998	0.998	0.999	0.997
CC ($\alpha = 0.9$)	0.998	0.998	0.996	0.999	0.996

5. **Conclusions.** It is seen from the MCDM model combining both cardinal and ordinal factors for selecting FMS that at lower level-of-satisfaction (α) the chances of getting involved higher degree of fuzziness (β) increase. Therefore, a decision maker's (DM) level-of-satisfaction should be at least moderate in order to avoid higher degree of fuzziness while making any kind of decision using the MCDM model.

One underlying assumption of the MCDM methodology was that the selection is made under certainty of the information data. In reality, the information available is highly uncertain and sometimes may be under risk also. The fuzzy S-curve MF helps in reducing the level of uncertainty as validated further by introducing the MLEANN framework shown in Table 6. It is found that within the MLEANN framework the decision depicted in Table 5 can be consolidated at an α value $= 0.42$ of the decision maker.

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