A comparative study of CHN-MNC, GA and PSO for solving constraints satisfaction problems

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Abstract. Our approach CHN-MNC, based Continuous Hopfield neural network and Min-Conflict heuristic), have proved that is more efficient than using CHN alone to solve Constraints Satisfaction Problem (CSP). In This paper we study the performance of CHN-MNC by comparing it robustness with two evolutionary algorithms. We choose a Genetic Algorithm and Swarm optimisation to performers this study. Some numerical experiments are done over a variety of problems to verify the efficiency and fast convergence of our approach. abstract needs to summarize the content of the paper.

Keywords: CSP, Metaheuristics, GA, PSO, Min-Conflict Heuristic.

1 Introduction

A large number of real world problems can be represented as constraint satisfaction problems (CSP). For example, scheduling, qualitative and symbolic reasoning, diagnosis, temporal andspatial planning, hardware design and verification, real-time systems and robot planning. A CSP problem can be considered as of a finite set of variables, each one has a finite domain of values and a set of constraints. A solution to a CSP is a complete assignment of variables which satisfy all constraints. But, finding this solution on a finite domain is a NP-complete problem requiring a combination of heuristics and combinatory search methods in order to be solved in a reasonable time [1]. In general, approaches to solve CSPs can be classified in two main categories: exact approaches and heuristic ones. As for exact approaches, most of them have the backtracking algorithm (BT) as a main algorithm for solving constraint satisfaction problems. As far as heuristic approaches are concerned, we find a very different approach has taken investigating neural approach works to solve CSP[2]–[4]. In this neural network approach, the constraints are encoded in the network topology, biases strengths connection, and problem is formulated as quadratic cost function which is a Lyapunov function. Particularly, a very different approach has been taken investigating Hopfield network with continuous times for solving CSPs, as we can see in [5]–[8] authors propose mapping CSP to a quadratic model and giving appropriate parameters setting to reach an equilibrium point of CHN. In the practice, there are two important problem with approaches based on conventional neural network architectures, The first is that network is

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partially mitigate the problem of getting stuck in local optimum, the second is due to dynamic Hopfield network which continuously explore the search space and will not stabilize at border 0 or 1, if the same case appear, we get low solution quality or an incomplete assignment of variables. In order to improve solution or to complete invalid solution, we propose to use Min-Conflict heuristic [8] after that CHN reached stabilisation. In this paper we extend our previous study by comparing CHN-MNC with Genetic algorithm [9] and Swarm optimisation [10].

2 CHN-MNC Algorithm

CHN-MNC is a collaborative hybrid algorithm, which benefit of the fast convergence of Hopfield neural network and the amelioration of the solution quality by the local search [11]

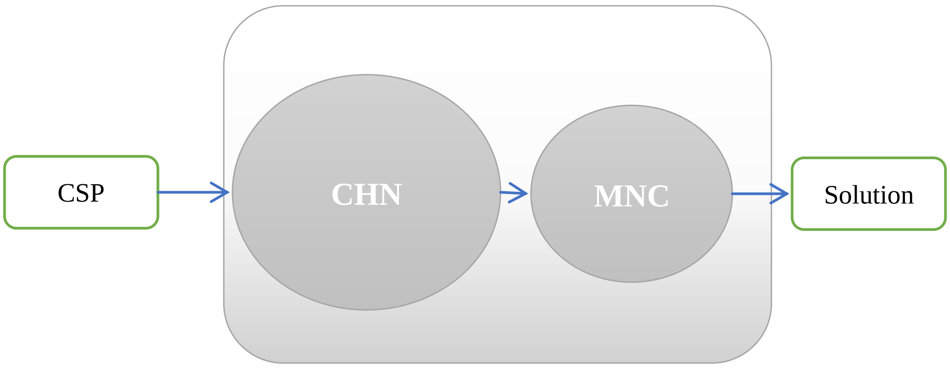

Fig. 1. Architecture CHN-MNC

2.1 CHN solver

A large number of real problems such as artificial intelligence, scheduling, assignment problem can be formulated as a Constraint Satisfaction Problem. Solving a CSP requires to finding an assignment of all variables problem under constraints restriction. The CSP can be formulated as three sets [12]:

- Set of N variables $X=\{X_i ; 1 \leq i \leq N\}$.
- Set of N variables domains: $D = \{D_i ; 1 \leq i \leq di\}$ where each Di contains set of di range values for X_i.
- Set of M constraints: $C = \{C_i ; 1 \leq i \leq M\}$.

Each constraint C_i associates an ordered variables subset which is called the scope of C_i. The arity of a constraint is the number of involved variables. We can easily reformulate CSP as a Quadratic Problem (QP), by introducing a binary variable x_{ik} for each CSP variable x_i, where k varies over the range of xi, given as follows:

$$x_{ik} = \begin{cases} 1, & if \;\; variable \; i \; takes \; value \; k \\ 0, & otherwise \end{cases} \tag{1}$$

For each binary constraint C_{ij} , between the variables y_i and y_j , we associate a state function defined as:

$$S_{ij}(x) = \sum_{r=1}^{d_i}\sum_{s=1}^{d_j} x_{ir} x_{js} Q_{irjs} \tag{2}$$

Where $x = \{x_{ik}, i \in [1 \dots N], k \in d_i\}$ a vector of QP solution and the quadratic terms Qirjs defined as:

$$Q_{irjs} = \begin{cases} 1 & if\,(r,s) \notin C_{ij} \\ 0 & otherwise \end{cases} \tag{3}$$

From all the equations defined in (2), which correspond to problem constraints, we deduce the objective function of its equivalent QP:

$$f(x) = \sum_{i=1}^{N}\sum_{r=1}^{d_i}\sum_{j=1}^{N}\sum_{s=1}^{d_j} x_{ir} x_{js} Q_{irjs} \tag{4}$$

Furthermore, some strict linear constraints equations must be satisfied by the solution: $\sum_{r=1}^{d_i} x_{ir} = 1$, for $i = 1..N$ which can be written also as $Ax = b$ (A is a $N \times M$ matrix and b is a M dimension vector fully initialized to 1). So, the model is given as follows:

$$(QP) \quad \begin{cases} Min \quad f(x) = x^T Q x \\ with \\ \qquad Ax = b \\ \qquad x \in \{0,1\}^n \end{cases} \tag{5}$$

Systematically, to solve the last Quadratic Optimization Problem with Hopfield model, we need to build an energy function such as the feasible solutions of the problem corresponding to the minimal of CHN energy function:

$$E(x) = \frac{\alpha}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{r=1}^{d_i}\sum_{s=1}^{d_j} xirx_{js} Q_{ijrs} + \beta\sum_{i=1}^{N}\sum_{r=1}^{d_i} x_{ir} + \gamma\sum_{i=1}^{N}\sum_{r=1}^{d_i} x_{ir}(1 - x_{ir}) \tag{6}$$

2.2 MNC local search

There are many methods which combine two or more no exacts approaches to solve a given optimization problem [13]–[16]. In the same direction we introduce a hybrid approach based CHN and MNC. The MNC algorithm [11] is a very simple and fast local repairing method to resolve CSPs, which aims at assigning all the variables randomly. Next, it iteratively selects one variable from the set of the variables with conflicts which violates one or more constraints of the CSP. Then, it assigns a value to the selected variable, so that it can minimize the number of conflicts. MNC has demonstrated to be able to solve the queens problem in minutes [17]. MNC is widely used to construct hybrid algorithms with other optimizations [14][15][18][19]. In this way, the basic idea of our proposed approach is to use MNC to improve the solution reached by CHN. This will be done in tw o steps (see Figure 2). First, MNC visits all assigned variables; for each one, we apply Min-Conflict directly to the neural network structure, then, it returns the best assignment for the current variable (see Figure 3), the decision will be taken by the sum of all activated neurons weight. Second, we propagate this assignment to other set variables not yet assigned iteratively by applying the MNC heuristic to guarantee as much consistency as possible. The diagram of our proposed algorithm is described by (Figure 4).

Function CHNMNC (CSP : **Problem**) :

- $V_a = CHN(CSPs)$
- **For** (each cluster $x_j \in V_a$) **do**
  - $V_a = V_a \setminus (x_j, a)$ {a is the current affected value to x_j }
  - $a = Min\text{-}Conf(x_j, V_a)$ { new value assigned to x_j }
  - $V_a = V_a \bigcup (x_j, a)$
- **end For**
- {propagate current sub assignment to other variables which not assigned }
- **For** (each cluster $x_j \notin V_a$) **do**
  - $a' = Min - Conf(x_j, V_a)$
  - $V_a = V_a \bigcup (x_j, a')$
- **end For**
- return V_a

End

Fig. 2. Main function which improve solution by Min-conflict algorithm

Function Min-Conf (x_i : **Current variable** , V_a : **Assigned variables set**) :

let x^*_{ir}: the current position which is assigned to the variable x_i
For (each value $v_k \in Dom(x_i)$) **do**
  $w(k) = \sum_{j \in V_a} x^*_{js} T_{ikjs}$
  { $x^*_{js} = 1$ is the position assigned to variable x_j}
end For
let W_{max} set of maximum output wait
If ($x^*_{ir} \in P_{max}$) **then**
  return r
else
  return random value from P_{max}
end If
End

Fig. 3. Selected the most coherent neuron of current cluster with other variables clusters already affected

3 Evolutionary Algorithm

The main problem with investing metaheuristic to resolve optimization problem is the probability of becoming trapped at locally optimal points. So, the combination and the cooperation between these approaches may improve the solution quality. Many hybrids approaches have been developed, for our case we shoos two intended, approaches, for solving CSP. The first, one is a combination with genetic algorithm and heuristics reproduction operators. The second is an adapted Swarm optimization to combinatory probes.

2.1 GA

We focus on hybrids algorithms which hybrids genetic algorithm with local search. Most all approaches use an integrative hybrid [14]–[16]. So, the Genetic algorithm is executed to the exploration of solution space and local search is used to improve the quality of each intermediate generation of population individual. Others make change on reproduction to adapted GA to a specific problem. In this work we opted for comparison with approach in [20]. The last method use a hybrid search approach that combines the genetic algorithm with the min-conflicts hill-climbing (MCHC).

2.1 Swarm

Collective intelligence refers to the capabilities of a resulting community of interactions multiple members (or agents) of the community. Agents can thus accomplish complex tasks through a fundamental mechanism called synergy. Under special conditions, the synergy created by the collaboration between individuals brings out the possibilities of representation, creation and learning superior to those of isolated individuals. The PSO parameters are specific to the problem to be solved and must be determined in each problem. The first work that employed the PSO for the resolution of the binary CSP problem was by Schoofs in [21]. The CSP problem is a combinatorial problem, where the concept of speed must be redefined. Thus, we present the redefinition of the usual operators of calculation (sum and product) between the positions and the speeds.

3 Numerical result

For showing the practical interest of our approach, we compares it its performance with others metaheuristics approaches over problems of different natures (random, academic and real-world problems). So we choose two algorithms elaborated specially to solve CSP [20], [21]. To perform a competitive comparison we do not settle for the authors original settings, thus we determined them empirically: for GA the population was 200 mutation rate equal to 5% and crossing rate equal to 72%, as for PSO [21] we choose $\varphi_1 = \varphi_2 = 1$ and population size fixed at 100. We run also 500 times each one.

We run some preliminary experiments on the randomly generated problems and we study the performances evolutions of the cited above approaches. We use a random generator based extended model B as it is described in [22]–[24]. This extended model which is called Model RB is able to generate a hard instance with forced mode which allow that instance have a solution. For each tightness value we generate 100 instances. From Figure 4 we can learn that our approach gives a good solution quality whatever the difficulty (Tightness) of the problem.

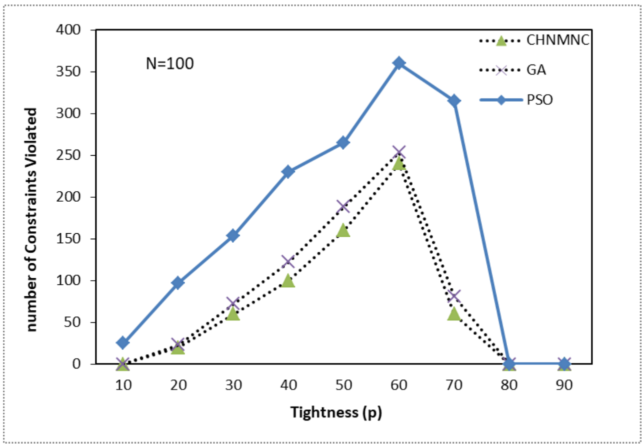

Fig. 4. Performance of GA, PSO and CHN-MNC random gendered instances.

Furthermore, Table 1 shows the results of CHN-MNC, PSO and Genetic Algorithm over 500 independent runs. The simulation is done on selected reals and academics instances of the benchmark [25]. According to the obtained means values our approach better and the standard deviation is more closed to the means values.

Table 1. Means values and standard deviation performed by CHN-MNC, GA, and PSO over selected instances.

Name of			CHN-MNC		GA		PSO	
Instance	V	C	Mean	SD	Mean	SD	Mean	SD
queens-10	10	45	1,01	0,16	2,00	1,02	13,50	5.5
queens-20	20	190,	2,40	0,32	4,00	1,06	39,20	3,11
queens-5-5-5	25	160	0,00	0,00	0,00	0,00	19,00	2,10
frb30-15-5-mgd	30	210	10,00	1,07	14,00	3.46	40,10	4,08
geom-30a-5	30	81	1,05	0,11	2,00	2,13	7,00	0,21
geom-30a-6	30	81	0,00	0,00	0,00	0,00	4,00	0,20
queens-30	30	435	4,00	0,94	6,00	1,05	83,00	7,39
frb40-19-3-mgd	40	308	14,00	0,93	21,00	2,14	53,00	3,56
geom-40-2	40	78	23,00	0,01	24,00	0,03	28,00	5,04
geom-40-6	40	78	0,00	0,00	0,00	0,21	4,01	1,06
myciel-5g-3	47	236	10,00	0,22	12,00	0,50	47,00	6,83
myciel-5g-4	47	236	5,00	0,41	8,00	0,95	29,00	3,58
myciel-5g-5	47	236	1,00	0,47	3,00	1,09	12,00	2,81
myciel-5g-6	47	236	0,00	0,13	1,00	0,31	12,50	1,51
driverlogw-01c	71	217	0,00	0,00	0,00	0,00	3,00	0,59
composed-25-10-20-5	105	620	13,10	1,93	14,00	6,75	56,00	7,20
dsjc-125-1-4	125	736	50,00	2,30	64,00	3,69	102,00	4,15
dsjc-125-1-5	125	736	19,00	1,80	29,00	1,83	85,00	4,04
Qw h-15-106-1	225	2324	20,00	1,60	23,00	3,68	66,60	5,11
qwh-15-106-4	225	2324	18,20	1,06	22,00	9,35	59,04	10,52
qwh-15-106-6	225	2324	22,00	2,31	23,00	5,31	68,00	8,82
driverlogw-04c	272	3876	3,00	2,32	5,00	2,33	11,00	3,75
driverlogw-02c	301	4055	3,00	1,17	5,00	1,89	9,00	2,01
qwh-20-166-0	400	5092	30,00	2,79	32,00	3,63	93,03	6,12
qwh-20-166-3	400	5092	29,00	1,88	31,00	2,63	89,00	4,28
qwh-20-166-6	400	5092	25,00	2,19	29,00	6,84	86,00	9,27
le-450-5a-3	450	5714	1173,00	5,69	1261,00	767,49	1566,00	17,03
le-450-5a-4	450	5714	712,00	1,89	745,00	8,95	1066,00	14,86
le-450-5a-5t	450	5714	441,00	2,29	470,00	5,26	874,00	13,72

3 Conclusion

In the last decade several areas have applied CSP model. So, many exact and heuristic methods were introduced. In this logic we focussed our contribution to develops a new hybrid approach based Hopfield neural network and local search. The main contribution in this work is the amelioration by the of the solution given by CHN Some numerical examples assess the effectiveness of the theoretical results are shown in this paper, and also the advantages of this new approach which improve considerably the solution quality and avoid network crush. Other studies are in progress to apply this approach to many problems such as timetabling and resource allocation.

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