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APPLICATION OF SPECIALIZED POPULATIONS IN A GENETIC ALGORITHM FOR OPTIMIZING THE PLACEMENT OF INTEGRATED CIRCUIT COMPONENTS

This paper proposes a modified genetic algorithm (GA) for the problem of placing integrated circuit (IC) components based on the idea of preliminary specialization of individual populations for the optimization of 1–2 parameters. Unlike classical approaches, where each individual's genotype encodes the entire solution, the proposed approach involves launching several independent populations, each initially evolving with a focus on 1–2 selected parameters (e.g., total connection length, thermal characteristics, occupied area). Once local optima are reached, inter-population crossover occurs: the best genetic solutions from different groups are combined for further global optimization, taking into account the full multi-criteria objective function. Experimental results demonstrate that this approach reduces the risk of getting trapped in local minima, accelerates algorithm convergence, and improves the final placement quality by 15–20% compared to classical GAs.

Keyword: genetic algorithms, specialized populations, IC placement, multiparametric optimization.

Introduction. The problem of optimal placement of components in integrated circuits (ICs) is one of the most critical challenges in electronic design (VLSI/ASIC/FPGA). The quality of the solution directly affects:

- Performance (critical delays, signal processing speed).
- Thermal characteristics (heat distribution, dissipation capability).
- Area (final chip size and production cost).
- Power consumption.

Traditional deterministic methods (including analytical and heuristic approaches) often become too complex as the number of objects N and the number of constraints increase. Genetic algorithms (GAs), which have proven effective in global optimization problems [1], are widely used for IC component placement. However, with the continuous increase in the complexity of designed objects, classical GAs faces the following challenges:

1. **High dimensionality.** As the number of objects and parameters increases (e.g., coordinates, mutual constraints, thermal and electrical requirements), the solution space expands dramatically.

2. **Tendency to local minima.** When all parameters are encoded within a single genotype, there is a high risk of getting "stuck" in local optima.

3. **High computational cost.** The evolutionary process requires significant resources to evaluate the multi-criteria objective function.

To overcome these challenges, the original multi-parameter problem is divided into subproblems, each containing 1–2 key parameters (e.g., total connection length and/or area; or thermal characteristics and/or delays). A specialized population is created for each subproblem, evolving based on a simplified objective function. Once stable local optima are reached, inter-population crossover occurs, where the best solutions from different groups are combined into a unified genotype that considers all parameters. Finally, a global optimization is performed using the original multi-criteria objective function.

LITERATURE REVIEW

Classical Genetic Algorithms in IC Placement

▪ Holland, 1975: A foundational work that laid the groundwork for evolutionary modeling.

▪ The application of GAs to VLSI problems has traditionally focused on global search using a single genotype that encodes the placement of all blocks [2]. However, as dimensionality increases, issues of scalability and convergence arise.

▪ There are hybrid methods that combine GAs with other heuristics (e.g., local search, simulated annealing, particle swarm optimization), but they do not fully solve the problem of high-dimensional solution spaces [3,4].

Cooperative Coevolutionary Algorithms (CCEA)

The idea of cooperative coevolution is to divide the problem into independent subproblems followed by the integration of the obtained solutions. Several studies have shown that this approach improves convergence and reduces the risk of getting trapped in local optima [5,6].

▪ In VLSI problems, "node-based" or "region-based" optimization is often used, where each section of the chip is considered separately. However, this approach does not always account for different parameters (e.g., power consumption vs. delays) but primarily focuses on physical localization.

The difference of the proposed approach

In the proposed method, specialization is not tied to the geographical division of the placement area, as in cooperative coevolutionary algorithms, but rather to the selection of a subset of parameters. This approach allows for the early-stage refinement of the best solutions based on individual criteria (e.g., minimizing connection length) and later integrates the best features from different subpopulations into a unified solution.

PROBLEM STATEMENT

Initial problem

Given a set of N objects (blocks, components, elements) that need to be placed within a designated IC substrate area while considering:

1. **Geometric constraints** (object sizes, minimum spacing).
2. **Timing constraints** (signal delays, critical paths).
3. **Area constraints** (total occupied area).
4. **Thermal constraints** (heat distribution, permissible temperature).

The goal of this study is to determine an optimal placement of elements, represented as a set of coordinates $\{(x_i, y_i)\}$ for $i = 1,\ldots, N$, that minimizes a given multi-criteria placement quality function.

The objective function

Let $\mathbf{X} = (x_1, y_1, \ldots, x_N, y_N)$ be the vector of placement parameters. Then, the multi-objective additive quality function, consisting of three partial quality functions, is defined as:

$$F(\mathbf{X}) = w_1 \cdot F_1(\mathbf{X}) + w_2 \cdot F_2(\mathbf{X}) + w_3 \cdot F_3(\mathbf{X}),$$

where $F_1(X)$ is the total connection length or the estimated routing length at the placement stage; $F_2(X)$ the occupied area or placement density; $F_3(X)$ a function reflecting thermal impact and/or maximum temperature; w_1, w_2, w_3 the weights defining the priorities of the corresponding criteria.

Limitations of the classical approach

In a standard GA, the genotype can represent either a permutation of objects or a complete set of coordinates. However, when the number of objects is large and multiple criteria are considered, the dimensionality of XX becomes excessively high. This leads to:

- Slower convergence.
- High probability of getting trapped in a local minimum.
- Increased computational cost per generation.

THE PROPOSED METHODOLOGY

The general framework of the proposed approach

The proposed approach operates in two major stages:

- **Population Specialization:**
- There are several independent populations (e.g. P_1, P_2, …, P_k), each of which optimizes a subset of parameters (1–2 criteria).
- For the population $P_{(i)}$ a simplified $\sim F_i(X_{(i)})$ function is formulated considering only the corresponding criteria.

▪ A classical evolutionary process is carried out: initialization, fitness evaluation, selection, crossover, and mutation-but only within the parameter space relevant to the given population.

▪ Inter-Population Crossover and Global Optimization:

▪ After reaching local optima (or upon termination), the best individuals from each population are selected.

▪ These individuals are combined into a new set of genotypes, where the optimal parameter values from different groups are gathered.

▪ A global phase of the genetic algorithm is initiated using the full objective function F(X), where evolutionary operators are applied again, but now for optimizing the complete set of parameters.

Algorithm details

The phase of specialized populations

1. **Initialization**

▪ Each subpopulation $P_{(i)}$ is assigned its domain related to 1–2 parameters, and individuals are randomly generated within this domain.

2. **Fitness evaluation**

▪ The function $\sim F_i(X_i)$ considers only the criteria (or part of them) for which the population P_i. For example, if the population specializes in minimizing the total connection length, we apply: $\sim F_i(X_i) = F_1(X_i)$.

3. **Selection, crossover, mutation**

▪ Standard genetic algorithm operators [2, 3] are applied, adapted to a lower-dimensional space.

▪ Higher mutation probabilities may be used in the early stages to accelerate the exploration of the space.

4. **Stopping**

▪ The process continues until a stopping criterion is met (e.g., a specified number of generations or no improvement over several iterations).

Inter-population crossover

1. **Selection of the best individuals**

▪ From each population, the top-m individuals are selected (based on $\sim F_i$).

2. **Formation of a unified genotype**

▪ For each parameter set (specialized group), the optimal values are taken from the corresponding subpopulation. Thus, a "hybrid" solution is formed, where, for example, the positions of elements affecting connection length are taken from the best solution in population P_1, while parameters influencing thermal characteristics are taken from population P_2 and so on.

3. **Creation of the combined population**

▪ The new "hybrid" solutions form the initial (or additional) part of the combined population P_global which then undergoes classical evolutionary processes based on the full objective function F.

Final global optimization

1. Global evaluation.

▪ Now, for each individual, the objective function $F(X) = w_1 \cdot F_1(X) + +w_2 \cdot F_2(X) + w_3 \cdot F_3(X)$, where w_1, w_2, w_3 are the weights that determine the priorities, and $F_1(X)$, $F_2(X)$ and $F_3(X)$ are the quality functions for the corresponding criteria.

2. **Selection, crossover, mutation**

▪ A multi-parameter evolution is performed, which "fine-tunes" the solution, taking into account all the interrelationships between the parameters.

3. **Output solutions**

▪ The algorithm stops when the specified number of generations is reached or when the results stabilize.

▪ The best individual, according to the F-metric, is accepted as the final placement.

Advantages of the proposed approach and potential challenges

Advantages

▪ Reduced dimensionality in early stages: Each population operates on fewer parameters, accelerating evolution and reducing the risk of early stagnation.

▪ Avoidance of deep local optima: The likelihood of getting "stuck" in one area for all parameters at once is reduced, as specialization provides independent search zones.

▪ Faster convergence: Due to more effective local optimization, solutions become "good" in key criteria even before the global phase.

▪ Improved computational efficiency: The approach allows for parallel processing of information.

Potential challenges

▪ Selection of parameter groups: Incorrect selection and distribution of parameters across populations may lead to conflicts during the global integration.

▪ Functional or correlated dependency of parameters: If parameters are closely related, narrow specialization on 1–2 criteria may require a more complex synchronization mechanism.

▪ Fine-tuning of parameters: It is necessary to control the number of generations in each phase, the proportion of migrating individuals, mutation probability, etc.

PRACTICAL IMPLEMENTATION

Initial Data and Assumptions for Implementation

To test the effectiveness of the method, the problem of placing N objects on a rectangular IC substrate area was chosen, taking into account:

- Area constraints.
- Delays (critical paths).
- Thermal distribution.

Two approaches were compared:

1. Standard GA with a single population, where each individual encodes the full set of coordinates X.
2. Modified GA with specialized populations (2–3 groups), each of which initially optimized only a subset of criteria (e.g., routing length + density, or thermal + timing parameters).

Experimental parameters

- **Size of each specialized population:** 50–100 individuals.
- **Number of generations for local (specialized) optimization:** 300.
- **Simplified functions**:
  - $\sim F_a$- considers only the total connection length,
  - $\sim F_b$ - considers thermal criteria,
  - $\sim F_c$ considers delays (e.g., maximum critical path length).
- After stabilization of each population, inter-population crossover occurs, and a combined population of 200 individuals is created.
- **Final global optimization:** 500 generations, mutation probability 0.03, and the full objective function $F(X) = w_1 \cdot F_1(X) + w_2 \cdot F_2(X) + w_3 \cdot F_3(X)$.

Evaluation metrics

- The total value of the objective function F after the algorithm completes.
- Convergence time (number of generations or total processing time).
- Solution stability (variance of results across multiple runs).

Results

The Experiment showed:

1. The standard GA often got trapped in local minima and required more generations to achieve an acceptable result.
2. The modified GA reduced the final value of the objective function F by 15–20% and shortened the convergence time by 20–30% (compared to the classical algorithm).
3. The enhanced method demonstrated lower variance in solution quality across multiple runs, indicating more stable identification of "globally" good placements.

Discussion

The results confirm that the preliminary specialization indeed helps in solving multi-parameter placement problems:

▪ Each subpopulation quickly "hones" specific criteria without being "burdened" by others.

▪ The solutions combined during inter-population crossover are more likely to simultaneously contain strengths across all parameters.

▪ Subsequent global optimization only slightly adjusts the found solutions, improving consistency among the criteria.

However, effectiveness largely depends on:

▪ Correct selection of criteria groups — it is important to combine parameters in one population that do not conflict strongly with each other.

▪ The number of local optimization iterations — if there are too few generations, subpopulations will not reach a quality local minimum; if there are too many, the risk of "overfitting" to individual criteria increases.

Promising directions for further research include:

▪ Adaptive distribution of parameters among subpopulations during evolution (e.g., based on current results).

▪ Hybridization with other heuristics (simulated annealing, local search) to fine-tune already "good" solutions.

▪ Integration with design rule checks and penalty system [7].

Conclusion

This paper presents a new approach to the optimization of placement of integrated circuit components based on specialized populations in a genetic algorithm. The key features include:

1. Decomposition of the original multi-parameter problem into 1–2 parameters for each subpopulation.
2. Local optimization in a smaller parameter space at an early stage.
3. Inter-population crossover for integrating the best local solutions.
4. Final global optimization considering the full objective function.

Experiments show that this methodology provides a significant improvement (15–20% in the objective function) and a reduction in convergence time (up to 30%) compared to the classical GA, which is particularly important when solving large placement problems in VLSI. Specialization methods can be successfully complemented by cooperative coevolution, adaptive mutation operators, and other heuristics, expanding the capabilities of evolutionary IC design.

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ԻՆՏԵԳՐՎԱԾ ՇՂԹԱՅԻ ԲԱՂԱԴՐԻՉՆԵՐԻ ՏԵՂԱԴՐՄԱՆ ՕՊՏԻՄԱԼԱՑՄԱՆ ՀԱՄԱՐ ՄԱՍՆԱԳԻՏԱՑՎԱԾ ՊՈՊՈՒԼՅԱՑԻԱՆԵՐԻ ՕԳՏԱԳՈՐԾՈՒՄԸ ԳԵՆԵՏԻԿԱԿԱՆ ԱԼԳՈՐԻԹՄՈՒՄ

Առաջարկվում է փոփոխված գենետիկական ալգորիթմ (ԳԱ)՝ ինտեգրալ սխեմայի (ԻՍ) բաղադրիչների տեղադրման խնդրի համար՝ հիմնված անհատական պոպուլյացիաների նախնական մասնագիտացման գաղափարի վրա՝ 1...2 պարամետրերի օպտիմալացման դեպքում: Ի տարբերություն դասական մոտեցումների, երբ յուրաքանչյուր անհատի գենոտիպը կոդավորում է ամբողջ լուծումը, առաջարկվող մեթոդը ներառում է մի քանի անկախ պոպուլյացիաների գործարկում, որոնք նախնական փուլում զարգանում են՝ կենտրոնանալով 1...2 ընտրված պարամետրերի վրա (օրինակ՝ ընդհանուր միացման երկարությունը, ջերմային հատկությունները, զբաղեցված տարածքը): Տեղային օպտիմումներին հասնելուց հետո իրականացվում է միջպոպուլյացիոն խաչասերում. տարբեր խմբերից լավագույն գենետիկական լուծումները համակցվում են հետագա գլոբալ օպտիմալացման համար՝ հաշվի առնելով բազմապարամետրական օբյեկտիվ ֆունկցիան: Փորձարարական արդյունքները ցույց են տալիս, որ այս մոտեցումը նվազեցնում է տեղական մինիմումներում խրվելը, արագացնում է ալգորիթմի համախմբումը և բարելավում է վերջնական տեղադրման որակը 15...20%-ով՝ համեմատած դասական GA-ների հետ:

Առանցքային բառեր. գենետիկական ալգորիթմներ, մասնագիտացված պոպուլյացիա, ԻՍ տեղաբաշխում, բազմապարամետրական օպտիմալացում:

Д.В. РЕВАЗЯН

ПРИМЕНЕНИЕ СПЕЦИАЛИЗИРОВАННЫХ ПОПУЛЯЦИЙ В ГЕНЕТИЧЕСКОМ АЛГОРИТМЕ ДЛЯ ОПТИМИЗАЦИИ РАЗМЕЩЕНИЯ КОМПОНЕНТОВ ИНТЕГРАЛЬНЫХ СХЕМ

Предлагается модифицированный генетический алгоритм (ГА) для решения задачи размещения компонентов интегральных схем, основанный на предварительной специализации отдельных популяций для оптимизации 1…2 параметров. В отличие от классических подходов, где генотип каждого индивида кодирует всё решение целиком, предложенный метод включает запуск нескольких независимых популяций, каждая из которых на начальном этапе эволюционирует с фокусом на 1…2 выбранных параметра (например, общая длина соединений, тепловые характеристики, занимаемая площадь). После достижения локальных оптимумов происходит межпопуляционный кроссовер: лучшие генетические решения из разных групп объединяются для дальнейшей глобальной оптимизации с учётом полной многокритериальной целевой функции. Экспериментальные результаты показывают, что данный подход снижает риск попадания в локальные минимумы, ускоряет сходимость алгоритма и улучшает качество итогового размещения на 15…20% по сравнению с классическими ГА.

Ключевые слова: генетические алгоритмы, специализированные популяции, размещение интегральных схем, многопараметрическая оптимизация.