A Low-Complexity Scheme to Reduce the PAPR of an OFDM Signal Using Taguchi-Genetic Algorithms

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Abstract

In this paper, we proposed a weighting factor estimation method for peak-to-average power ratio (PAPR) based on Taguchi-genetic algorithm (TGA) in an orthogonal frequency division multiplexing (OFDM) systems. Partial transmit sequences (PTS) is one of the most attractive schemes to reduce the PAPR in OFDM systems. However, the conventional PTS scheme requires an exhaustive searching over all combinations of allowed phase factors. Consequently, the computational complexity increases exponentially with the number of the subblocks. In this study, a new PTS technique that uses a novel numerical stochastic optimization algorithm inspired from natural genetics and natural selection, designated as hybrid Taguchi-genetic algorithm (HTGA), for PAPR reduction in the OFDM system is introduced. The simulation results show that compared with the various stochastic search techniques developed previously, the proposed TGA-based PTS obtains the excellent PAPR performance with a low computational complexity.

Keywords: Orthogonal frequency division multiplexing (OFDM), hybrid Taguchi-genetic algorithm (HTGA), Peak-to-average power ratio (PAPR) reduction, and Partial transmit sequence (PTS) 。

1. Introduction.

Orthogonal frequency division multiplexing (OFDM) has many well known advantages such as robustness in frequency-selective fading channels, high bandwith efficiency, efficient implement, and so on [1-4]. However, a major problem associated with multicarrier modulation is its large peak-to-average power ratio (PAPR) [4]–[8], which makes system performance very sensitive to distortion introduced by nonlinear devices such as power amplifiers. Hence, to alleviate this problem, many PAPR reduction techniques have been proposed in the literature, cf. e.g. [4] for an overview.

In current techniques, partial transmit sequence (PTS) scheme [7-14] has been proved efficient and distortionless, in which multiple candidate signals are generated to reduce the PAPR but with the side effect of high complexity. In order to reduce the complexity, some simplified techniques have been proposed [7-9]. Most of them focus on reducing the number of candidate signals. In general, the complexity of PTS is proportional to the number of candidate signals. However, in individual candidate signal, the complexity for combining the phase weight factor and computing the PAPR still remains high.

In this paper, we take a fresh look at PTS for PAPR reduction and propose solutions for both the above-mentioned problems. To tackle the complexity issue of PTS, we formulate the sequence search of PTS as a particular combinatorial optimization (CO) problem. To reduce complexity for phase weight searches, some stochastic search techniques have recently been proposed because they could obtain the desirable PAPR reduction with a low computational complexity. The Artificial Bee Colony Algorithm [15], simulated annealing (SA) algorithm [16-17], Ant colony optimization (ACO), Crooss-Entropy (CE) method [18], Neural Networks [19], Genetic algorithm (GA) [20-21] and particle swarm optimization (PSO) [22-23], etc. have been applied to solve the PAPR reduction problems. Among the existing optimization algorithms, the traditional genetic algorithm (TGA) has received considerable attention regarding its potential as a novel optimization technique for complex problems and has been successfully applied in various areas [24]. Although the TGA is a very valid in solving engineering problems as far as optimization, when the dimensions of the problem are high and there are numerous local optima, a particular challenge has shown that the TGA may be trapped in the local optima and produces different values in each run. In this work, we extend the TGA algorithm for handling PAPR problems.

In this paper, a hybrid Taguchi-genetic algorithm (HTGA) [24-27] is proposed to solve global numerical optimization problems with continuous variables. The HTGA combines the traditional genetic algorithm (TGA), which has a powerful global exploration capability, with the Taguchi method, which can exploit the optimum offspring. The Taguchi method [28] is inserted between crossover and mutation operations of a TGA. Then, the systematic reasoning ability of the Taguchi method is incorporated in the crossover operations to select the better genes to achieve crossover, and consequently, enhance the genetic algorithm. Moreover, in this paper, the GA approach is applied to solve optimization problems in a method developed by Dr. Jyh-Horng Chou [24-27] to resolve the problem in the search the sub-block partition style and the value of phase weighting factor set could be well-designed to obtain the candidate signals with a reducing correlation to improve the PAPR reduction performance. Hence, with applying the HTGA algorithm into the PTS scheme, it could provide a way to reduce the PAPR of OFDM transmitted signal. The performance evaluation of the proposed scheme for PAPR reduction and computation complexity is given in this paper.

The reminder of this paper is organized as follows. Section 2 briefly describes the conventional OFDM system and its PAPR problem is described. Besides, the conventional PTS is introduced. Then, hybrid Taguchi-genetic algorithm (TGA) is applied to search the optimal combination of phase weighting factors for PTS scheme in Section 3. In Section 4, the performance on PAPR reduction for the proposed scheme is presented. Finally, the conclusion is given in Section 5.

2. System Model and Problem Definition

An OFDM signal consists of the sum of independent signals modulated in the frequency domain onto subchannels of equal bandwidth. The OFDM signal is expressed as

$$x_n = \frac{1}{\sqrt{N}} \sum_{i=0}^{N-1} X_i e^{j2\pi ti/N}, 0 \le n \le N-1 \qquad (1)$$

where $X_i, i = 0,1,\cdots,N-1,$ are input data symbols modulated by BPSK, N is the number of subcarriers and x_n is transmitted signal. The PAPR of the transmitted signal in Eq.(1) could be defined as

$$PAPR(x) = 10\log_{10} \frac{\max\limits_{0\le n\le N-1} |x_n|^2}{E\left[|x|^2\right]}, \qquad (2)$$

where *max* $\max|x_n|^2$ is the maximum values of the OFDM signal power, $x = [x_0, x_1, \cdots, x_{N-1}]^T$ and $E[\cdot]$ denotes the expected value operation. In principle, PAPR reduction techniques are concerned for reducing $\max|x_n|^2$. By applying the central limit theorem with assuming that the number of sub-channels is sufficiently large, the time domain symbol is approximately zero-mean complex Gaussian distributed and the power distribution becomes a central chi-square distribution with two degrees of freedom.

In the PTS technique, an input data a block of N symbols is partitioned into disjoint sub-blocks. The subcarriers in each sub-block are weighted by a phase weighting factor for the sub-block. The phase weighting factors are selected such that the PAPR of the combined signal is minimized. Besides, for PAPR reduction, the PTS scheme can be easily combined with the corresponding symbol transform scheme. The block diagram of TGA-based PTS scheme is shown in Fig. 1. In the scheme, it requires to divide data block into sub-blocks or clusters and, then, multiply the appropriate phase weighting factors to each sub-blocks for PAPR reduction. The data block is defined as a vector $\mathbf{X} = [X_1 \quad X_2 \ldots \quad X_N]^T$. Then, X is partitioned into M disjoint sub-blocks represented by the vector X such that

$$\mathbf{X} = \sum_{i=1}^{M} \mathbf{X}_i \,. \qquad (3)$$

Here, it is assumed that the clusters $\mathbf{X}_i$ consist of a set of sub-blocks with equal size. The objective is to find sets of phase weight factors b .Then, the weighted sum combination of the M sub-blocks which could be written as

$$Z(b)=\sum_{i=1}^{M} b_i \mathbf{X}_i, \quad b_i = e^{j\phi_i}\ . \qquad (4)$$

where b_i, i=1, 2,…., M is the phase weighting factor with phase factor $\varphi_i = 0$ or 2π commonly. In general, the selection of the phase weighting factors is limited to a set with finite number of elements to reduce the search complexity. After transforming to the time domain, the new time domain vector becomes

$$\mathbf{x} = IFFT\left\{\sum_{i=1}^{M} b_i \mathbf{X}_i\right\} = \sum_{i=1}^{M} b_i IFFT\left\{\mathbf{X}_i\right\} \qquad (5)$$

The optimization process is to find phase weighting factor that minimize the PAPR. The optimal phase weighting factor b_i that minimizes the PAPR can be obtained from a comprehensive simulation of all possible b^{M-1} combination. The objective of the proposed method is to choose a phase weighting vector $\mathbf{b} = \{b_1,\ \mathrm{b}_2, \cdots, b_i\}$ to reduce the PAPR of $Z(b)$, and the cost function is defined as

$$\hat{\mathbf{b}} = \arg\ \min_{b}\left\{\max\left|\sum_{i=1}^{M} b_i \mathbf{X}_i\right|\right\}. \qquad (6)$$

and $b \in \{0,1\}^K$ is the set of K-dimensional binary vectors. It is obvious that finding the optimum solution of (6) is a difficult optimization problem with the complexity of $O(2^K)$. Therefore, a novel implementation of PAPR reduction problem in (6) using the TGA method in next section is proposed.

3. The Hybrid Taguchi-genetic algorithm -based PTS scheme for Reduction PAPR

A. The Taguchi Method

In this section, we briefly introduce the basic concept of the structure and use of two-level orthogonal arrays. The Taguchi method [26-28]uses a special design of orthogonal arrays (OAs) to study the entire parameter space using a small number of experiments only. The experimental results then are transformed into a signal-to noise ratio (SNR) to evaluate the performance. Therefore, the Taguchi method is to concentrate on the effects of variations on a product or on process quality characteristics rather than on its averages. That is, the Taguchi method makes the product or process performance insensitive to the variations of uncontrollable noise factors. According to certain derived standard OAs, two or more parameters can be simultaneously and independently evaluated in a minimum number of tests for their abilities to affect the variability of a particular product or process characteristic. Subsequently, a decision can be made for the optimum combination of these parameters.

An orthogonal array is fractional factorial matrix, which assures a balanced comparison of levels of any factor or interaction of factors. It is a matrix of numbers arranged in rows and columns where each row represents the level of the factors in each run, and each column represents a specific factor that can be changed from each run. The array is called orthogonal because all columns can be evaluated independently of one another. The general symbol for two-level standard orthogonal arrays is $L_n\left(2^{2n-1}\right)$ .where $n = 2^k$ number of experimental runs; k a positive integer which is greater than 1; number of levels for each factor; n - 1 number of columns in the orthogonal array.

The letter "L" comes from "Latin," the idea of using orthogonal arrays for experimental design having been associated with Latin square designs from the outset. Two-level standard orthogonal arrays most often used in practice are $L_4\left(2^3\right)$, $L_8\left(2^7\right)$, $L_{16}\left(2^{15}\right)$, and $L_{32}\left(2^{31}\right)$. Table I shows an orthogonal array $L_8\left(2^7\right)$.The number to the left of each row is called the run number or experiment number and runs from 1 to 8.

In the field of communication engineering, a quantity called the SNR (η) has been used as the quality characteristic of choice. Taguchi [29], whose background is communication and electronic engineering, introduced this same concept into the design of experiment. Two of the applications in which the concept of SNR is useful are the improvement of quality via variability reduction and the improvement of measurement. The control factors that may contribute to reduced variation and improved quality can be identified by the amount of variation present and by the shift of mean response when there are repetitive data. The SNR transforms several repetitions into one value, which reflects the amount of variation present and the mean response. There are several SNRs available depending on the type of characteristic: continuous or discrete; nominal-is-best, smaller-the-better, or larger-the-better. Here, we will only discuss the continuous case when the characteristic is smaller-the-better or larger-the-better. In the case of smaller-the-better characteristic, suppose that we have a set of characteristics $y_1, y_2, \ldots, y_n$. Then, the natural estimate is $S = \frac{1}{2}\sum_{t=1}^{n} y_t^2$ where S denotes the mean squared deviation from the target value of the quality characteristic. Taguchi recommends using the common logarithm of this SNR multiplied by 10, which expresses the ratio in decibels (db); this has been used in communications for many years. To be consistent with its application in engineering, the value of the SNR (η) is intended to be large for favorable situations, and we use the following transformation for the smaller-the-better characteristic: $\eta = -10\log\left(\frac{1}{n}\sum_{t=1}^{n} y_t^2\right)$.

A. *Generation of Initial Population*

In the real coding representation, each chromosome is encoded as a vector of floating-point numbers, with the same length as the vector of decision variables. The real coding representation is accurate and efficient because it is closest to the real design space, and, moreover, the string length is the number of design variables. However, binary substrings representing each variable with the desired precision are concatenated to represent an individual, the resulting string encoding a large number of design variables would wind up a huge string length.

We use vector $(x_1, x_2, \cdots, x_i, \cdots, x_N)$ as a chromosome to represent a solution to the optimization problem. Initialization procedure produces M chromosomes, where M denotes the population size, by the following algorithm.

B. *Generation of Diverse Offspring by Crossover Operation*

The crossover operators used here are the one-cut-point crossover integrated with an arithmetical operator derived from convex set theory which randomly selects one cut-point, exchanges the right parts of two parents after the cut-point, and calculates the linear combinations at the cut-point genes to generate new offspring. For example, let tow parents be $x = (x_1, x_2, \cdots, x_N)$ and $y = (y_1, y_2, \cdots, y_N)$. If they are crossed after the kth position, the resulting offspring are

$$x' = (x_1, x_2, \cdots, x_k', yk+1, yk+2, \cdots, yn)$$

$$y' = (y_1, y_2, \cdots, y_k', xk+1, xk+2, \cdots, xn)$$

where $x_k' = x_k + \beta(y_k - x_k)$, $y_k' = l_k + \beta(u_k - l_k)$, l_k and u_k are the domain of y_k, and β is a random value, in which $\beta \in \{0, 0.1, 0.2, \cdots, or\ 1\}$ .Therefore, the above process to generate the value of a gene similar to the process of using a randim value β of the uniform distribution with the fixed domain. Moreover, the method of dynamically extended precision mentioned above can search a solution from a low-precision solution space to a high-precision solution space. For the low-precision problem, the method can quickly find the solution in the low-precision solution space and then change to high precision, thus enhancing the efficiency of the algorithm.

C. *Generation of Better Offspring by Taguchi Method*

The orthogonal arrays of the Taguchi method are used to study large number of decision variables with a small number of experiments. The better combinations of decision variables are decided by the orthogonal arrays and the SNRs. The Taguchi concept is based on maximizing performance measures called SNRs by running a partial set of experiments using orthogonal arrays. In this study, a two-level orthogonal array is used. There are Q factors, where Q is the number of design factors(variables)and each factor has two levels. To establish an orthogonal array of Q factors with two levels, let $L_n(2^n - 1)$ represent $n-1$ columns and n individual experiments corresponding to the n rows, where $n = 2^k$, k=a positive integer $(k > 1)$, and $Q \le n-1$. Let $\eta_i = (y_i)^2$ or $(1/y_i)^2$ if the objective function is to be maximized (larger-the-better) or maximized (smaller-the-better), respectively. Let y_i denote the function evaluation value of experiment i and $i = 1, 2, \ldots, n,$ where n is the number of experiments. The effects of the various factors (variables) can be defined as following: E_{fl} = sun of η_i for factor f at level l. Where i is the experiment number, f is the factor name, and l is the level number.

After a crossover operation in the TGA, the two chromosomes from each run are randomly chosen to execute the matrix experiments of the orthogonal array. The primary goal in conducting this matrix experiment is to determine the best or the optimal level for each factor. The optimal level for a factor is the level that gives the highest value of E_{fl} in the experimental region. For a two-level problem, if $E_{f1} > E_{f2}$, the optimal level is level 1 for factor *f*. Otherwise, level 2 is the optimum one. After the optimal levels for each factor are selected, one also obtains the optimal chromosomes. Therefore, this new generation of offspring has the best or nearly the best function value among those of 2^Q combinations of factor level, where 2^Q is the total number of experiments needed for all combinations of factor levels.

D. Mutation Operation

When the designed variables converge at the same objective value, the level of mutation can be increased. The reason why the same value can be obtained is that the convex combination given below is calculated to make the value of two genes closer stepwise. For a given $x = (x_1, x_2, \ldots, x_i, x_j, x_k, \ldots, x_N)$, if the elements x_i and x_k are randomly selected for mutation, the resulting offspring is $x' = (x_1, x_2, \ldots, x'_i, x_j, x'_k, \ldots, x_N)$. The two new genes x'_i and x'_k are $x'_i = (1-\beta)x_i - \beta x_k$ and $x'_k = \beta x_i + (1-\beta)x_k$.

E. Hybrid Taguchi-Genetic Algorithm (HTGA)

The HTGA combines the TGA with the Taguchi method. Fig. 1 A block diagram of the TGA based PTS technique. The Taguchi method is inserted between crossover and mutation operations of a TGA. Then, the systematic reasoning ability of the Taguchi method is incorporated in the crossover operation to select the better genes to achieve crossover, and consequently enhance the GA. The steps of the HTGA approach are as follow.

Step 0) Parameter setting.

- Input: population size M, crossover rate p_c ,mutation rate p_m ,and number of generations.
- Output: the number of function evaluations and function value.

Step 1) Initial population is generated by the Algorithm given above. The function values of the population are then calculated via the test function. The number of function calls is calculated *M* times.

Step 2) Selection operation using the roulette wheel approach.

Step 3) Crossover operation. The probability of crossover is determined by crossover rate p_c.

Step 4) Select a suitable two-level orthogonal array for matrix experiments. The orthogonal arrays $L_{32}(2^{31})$ and $L_{128}(2^{127})$ are used for 30 and 100 dimensions, respectively.

Step 5) Chose randomly two chromosomes at a time to execute matrix experiments.

Step 6) Calculate the function values and SNRs of *n* experiments in the orthogonal array $L_n(2^{n-1})$.

Step 7) Calculate the effects of the various factors (E_{f1} and E_{f2}).

Step 8) One optimal chromosome is generated based on the results from Step7.

Step 9) Repeat Step 5 through 8 until the expected number $(1/2) \times M \times p_c$ has been met.

Step 10) The population via the Taguchi method is generated. The number of function calls is calculated $(1/2) \times M \times p_c \times (n+1)$ times, where $n+1$ comes from *n* experimental runs of an orthogonal array $L_n(2^{n-1})$ plus one run for the optimum chromosome generated by SNRs.

Step 11) Mutation operation. The probability of mutation is determined by mutation rate p_m .The expected number of function calls is calculated $(1/2) \times M \times p_c$ times.

Step 12) Offspring population is generated.

Step 13) Sort the fitness values in increasing order among parents and offspring populations.

Step 14) Select the better M chromosomes as parents of the next generation.

Step 15) Has the stopping criterion been met? If yes, the expected number of function calls is calculated

In this section, we proposed a novel implementation of the PTS scheme based on the HTGA algorithm [24-25]. Hybrid Taguchi-genetic algorithm (HTGA), first designed and developed by Dr. Jinn-Tsong Tasu and Dr. Jyh-Horng Chou [26-27], is a relatively novel numerical stochastic optimization algorithm inspired from . The algorithm is simple but has shown to be effective in converging to optimal solution by employing basic properties, e.g. seeding, growth and competition, in a weed colony [24]. In a D-dimensional search space, a weed which represents a potential solution of the objective function is represented by $\mathbf{b}=(b_1,b_2,\cdots,b_m)$. For a concrete understanding of the TGA, the reader is referred to [23-25] for more details.

4. **Results and Discussions.**

In this section, the system performance with applied proposed PTS scheme is evaluated based on the PAPR complementary cumulative distribution function (CCDF) and the bit error rate (BER) by computer simulation. The modulation is chosen as QPSK scheme and the number of sub-carriers is assumed to be 128 and the length of the spreading code is assumed to be 128. In the simulations, the random sub-blocks partitioning is used both in the conventional PTS and the proposed PTS schemes.

Fig. 2 show the variation in CCDF with the proposed HTGA method for different numbers of the maximum number of iterations, *G*, with *N* = 128, respectively. In the TGA method, the population size is assumed to be *P* = 20; and the corresponding maximum number of iterations are *G* =30. In addition, the exhaustive search algorithm (ESA) mentioned in [4-5] is presented to compare the performance of PAPR reduction with that of the HTGA searching method. In the ESA, the selection of the phase factors was limited to a set of finite number of elements *M*. The ESA was then employed to find the best phase factor. Here, four allowed phase factors ± 1, and $\pm j$ (*b* = 4) are used for the ESA, and the PAPR reduction performance is achieved by a Monte Carlo search with a full enumeration of Mb (4^8 = 65,536) phase factors. As shown in Fig. 3, as the maximum number of iterations is increased and, then, the CCDF of the PAPR has a better performance. When $P_r[PAPA>PAPR_0]=10^{-3}$, it shows that the performance of the proposed TGA based PTS method provides an approximate PAPR reduction as with that of the conventional ESA. The comparison is carried out under the same conditions of initial population of candidate solutions and number of iterations.

Next, the proposed TGA-based PTS scheme with other existing stochastic optimization-based PTS approaches for the same number of samples, *Sam* = 2000 is shown. Fig. 2 shows the CCDFs of the PAPR of the OFDM system using the SA, the greed method, Bee conoly, the proposed HTGA method, and the original OFDM with the number of subcarriers *N*=128. It can be seen that the PAPR of the original OFDM signal at $P_r[PAPA>PAPR_0]=10^{-4}$ for *N*=128 is 13.56 dB, which indicates a large PAPR. For *N*=128, the suppressed PAPRs of the GA, the Greed , the SA, Bee colony, and the proposed HTGA method at $P_r[PAPA>PAPR_0]=10^{-4}$ are 7.73, 7.56, 7.49, 6.41, and 6.25 dB, respectively.. Therefore, the proposed HTGA-based PTS method can offer better PAPR reduction while keeping a low complexity.

Fig. 3 shows the simulation results of four different methods on the mean of the best cost function values. In initial phase, the performance of the TGA-PTS is inferior to that of GA-PTS, SA-PTS, Bee-colony and Greed method. As the increase of iterations, the performance of the TGA-PTS is better than that of Bee colony-PTS and SA. Although the PAPR performance is improved with the increase of iteration number, the mean of PAPR getting by the iteration number *G* = 30 is only less 0.4 dB than that of PAPR getting by the iteration number *G* = 60, so iteration number *G* =30 can be a suitable choice for our proposed TGA-PTS algorithm.

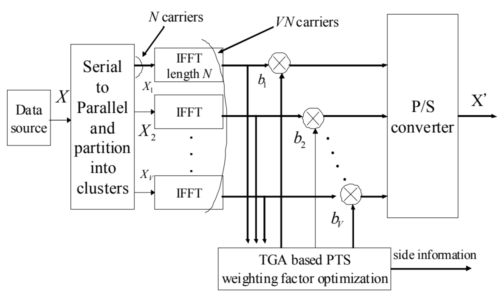

Fig. 1 A block diagram of the TGA based PTS technique.

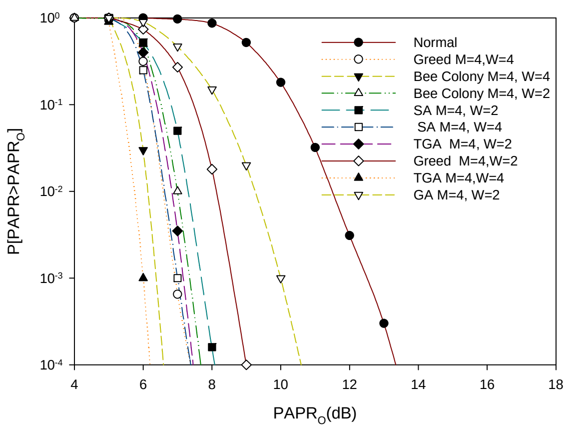

Fig. 2 Comparison of the PAPR CCDF of several PTS methods.

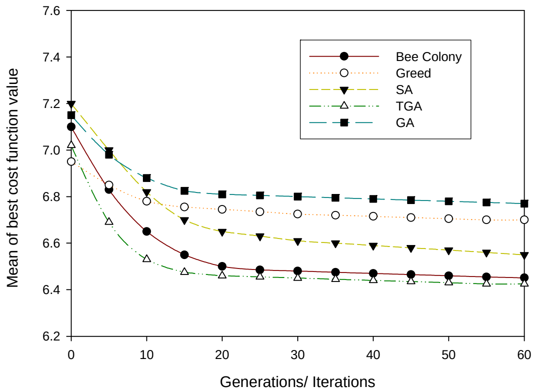

Fig. 3 Comparison of mean of best cost function values for different swarm intelligence methods.

4. Conclusions.

This paper proposes a HTGA technique applied to obtain the optimal phase weighting factor for the PTS scheme to reduce computational complexity and improve PAPR performance. The searches on phase weighting factors of the PTS technique is formulated as a global optimization problem with bound constraints. Furthermore, the applied phase weight factors and the corresponding performance improvement for three subblock partitioning scheme-interleaved partition, adjacent partition and random partitioning have been well investigated. The computer simulation results show that the proposed TGA technique obtained the desirable PAPR reduction with low computational complexity when compared with the various stochastic search techniques. For its flexibility, i.e. the number of sub-blocks, the number of admitted angles and subblock partition scheme, the resulting peak power reduction can be achieved with several levels of the required PAPR.

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