IMPLEMENTATION OF GENETIC ALGORITHM TECHNIQUE FOR SOLVING ROP DETECTOR LAYOUT OPTIMIZATION PROBLEM

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Abstract

The regional overpower protection (ROP) systems protect CANDU® reactors against overpower in the fuel that could reduce the safety margin-to-dryout. The overpower could originate from localized power peaking within the core or a general increase in the core power level. The design of the detector layout for the ROP systems is a challenging discrete optimization problem. In recent years, two algorithms have been developed to find a quasi-optimal solution to this detector layout optimization problem. Both of these algorithms utilize the simulated annealing (SA) algorithm as their optimization engine. In the present paper, an alternative optimization algorithm, namely the genetic algorithm (GA), has been implemented as the optimization engine. The implementation is done within the ADORE algorithm. Based on this preliminary studies performed on four different sizes of ROP system, it has been demonstrated that the GA technique is able to produce good results.

1. Introduction

The regional overpower protection (ROP) systems in the CANada Deuterium Uranium (CANDU®[1]) reactor protect the reactor against overpower in the fuel which could originate from either a bulk power increase during a slow-loss-of-regulation (SLOR) event or from a more localized power peaking within the core (for example, due to certain reactivity device configurations). The overpower could lead to fuel sheath dryout which is a condition where the fuel is operating at temperatures higher than the desired temperature. During a dryout event the coolant around the fuel sheath surface produces many small bubbles that could eventually coalesce into a vapour film enveloping the fuel element. This reduces the heat transfer from fuel to the coolant and in turn further elevates the fuel temperature. If uncontrolled or undetected, this event could lead to fuel failures.

To protect the core from this fuel failure event, in the CANDU 600 MW (CANDU 6) design, there are two ROP systems where each system consists of three independent safety channels and is connected to a fast-acting shutdown system. These two systems use different mechanisms to shutdown the reactor and are physically separated (see Figure 1). More detailed descriptions of the ROP systems can be found in [1].

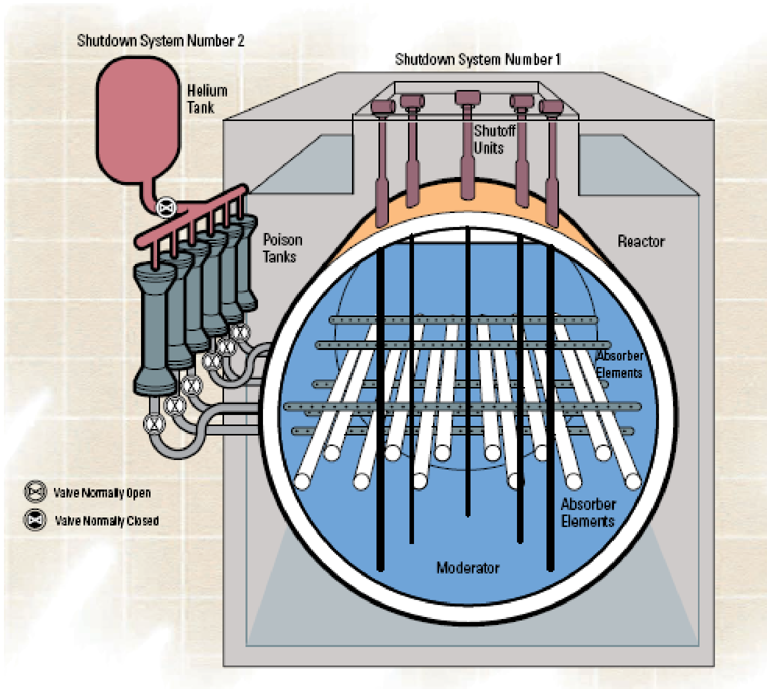

Figure 1. CANDU 6 Shutdown System.

The placement of the ROP detectors in the core is a challenging discrete optimization problem. The design for the current CANDU 6 plants were determined using a method called the detector layout optimization (DLO) [2]. Unfortunately, when the design process involves thousands of potential detectors and hundreds of flux shapes[2], the DLO methodology does not perform well. To circumvent this issue, in recent years the DETPLASA [1] and ADORE [3] algorithms have been developed. Both of these new algorithms employs the simulated annealing (SA) stochastic optimization technique [4] to come up with an optimized detector layout for the ROP system. It has been shown that both algorithms can produce a solution for a design problem where more than 500 flux shapes and more than 2000 candidate detectors are involved.

An alternative optimization technique, namely the genetic algorithm (GA), has been implemented within the ADORE algorithm to assess the performance of GA in solving the ROP detector layout optimization problem. For discussions within this is paper, this version of ADORE will be called ADORE-GA. The GA method is chosen for this evaluation since this method has been widely used in analysis for various reactor design such as the pressurized water reactor (PWR) ([5],[6],[7]), the boiling water reactor (BWR) ([8],[9]), the Canada Deuterium Uranium (CANDU) ([10],[11],[12]), VVER [13], and Liquid Metal Fast Breeder Reactor (LMFBR) [14].

[2] "Flux shapes" are various flux and power distributions caused by changes to device configuration (including zone-controller fills) or xenon distribution from the nominal distribution. The term "nominal" refers to normal operating core configuration where the average zone controller level is around 50%, the adjusters are fully inserted, and the mechanical control absorber rods as well as the shutoff rods are fully withdrawn. This configuration is defined as the nominal case since this is expected to be a representative average over the life of the reactor.

The following is how this paper is structured. A brief overview of the ROP trip set point (TSP) calculation using the ROVER-F code [15], a brief overview of the GA algorithm, and the current implementation within the ADORE algorithm are presented in Section 2. Some numerical results from executing ADORE-GA are presented in Section 3. Finally, Section 4 closes the paper with some conclusions.

2. Methodology

2.1. ROP TSP Calculations

The current safety requirement of an ROP system is that it must actuate a reactor trip before the onset of intermittent dryout (OID) in any fuel channel. It is physically prohibitive to detect the dryout of a fuel bundle among 4560 fuel bundles in a 380-channel CANDU 6 reactor. Instead of monitoring the OID directly, the ROP analyses are performed by monitoring two quantities called the margin-to-trip (MTT) and the margin-to-dryout (MTD). The MTT is defined as the ratio between the reactor power at which the ROP system will actuate the shutdown system and the actual reactor power. The MTD is defined as the ratio between the channel power at which dryout will first occur (the corresponding channel power level is called the critical channel power or CCP) and the actual channel power. The relation between these two quantities is the basic equation in the ROP analysis.

Mathematically, this basic ROP safety requirement can be described by the following inequality:

$$MTT \leq MTD \tag{1}$$

or

$$\frac{TSP}{\phi} \leq \frac{CCP}{CP} \tag{2}$$

where TSP is the trip set point, ϕ is the detector reading (appropriately normalized to 100% full power), CCP is the critical channel power and CP is the channel power.

2.1.1. Basic Equation (deterministic)

In the design and operation of the ROP systems, changes in the neutron flux distribution (and, hence power distribution) from the nominal can be categorized into two types: Flux Shapes and Fuelling Ripples. The basic ROP safety requirement can then be expanded to account for these two variations. The requirement is that for any flux shape k and ripple q, each safety channel must trip before the power in any fuel channel reaches the CCP for that fuel channel. This means that the detector locations, detector channelizations in the safety channel, and the TSP must be determined carefully such that for each flux shape considered, there is at least one detector $j_{p,i}$, in each safety channel i which satisfies the following expression:

$$TSP(j_{p,i}) \leq \phi(j,k) \times r_{CPRL}(k,q)\ , \tag{3}$$

where $TSP(j_{p,i})$ is the installed trip set point for protecting detector j (the subscript p is used to emphasize that it is a protecting detector), in logic channel i; and, $\phi(j,k)$ is the normalized detector reading at detector j for flux shape k (and may include various calibration terms depending on plant operation). The detector reading for each flux shape is normalized to the detector reading for the nominal flux shape and thus is invariant to fuelling ripple; and $r_{CPRL}(k,q)$ is the minimum critical power ratio (*i.e.*, the MTD) for flux shape k and fuelling ripple q. Symbolically it can be written as

$$r_{CPRL}(k,q) = \min_m \left\{ \frac{CCP(m,k)}{CP(m,k) \times RIP(m,q)} \right\} \tag{4}$$

where m is the fuel channel index and $RIP(m,q)$ is the ripple value for channel m for q fuelling ripple set.

In practice, there are some modifications to be made to Eq. (4) to account for the followings:

1. *Allowance for uncertainties*. The final trip set point for a given ROP design is determined by a trip probability calculation for each of the design-basis flux shapes. These are flux shapes that may occur during normal reactor operation. In this calculation, the TSPs are, in effect, adjusted until they meet the target trip probability for the pre-determined set of flux shapes.

2. *Fuelling Ripple*. The *RIP* term in Eq. (4) refers to the channel ripple which is defined as the ratio of observed (*i.e.*, snapshot from the plant operation) channel power to the nominal flux shape channel power.

3. *Calibration and channel power peaking factor (CPPF).* Ripples and, hence, the corresponding CPPF (which is the maximum value of channel ripples for a particular snapshot) are tracked during operation and relevant factors are applied to the detector readings. It should be noted that the detector calibration factor is plant specific.

To account for these modifications, the protection equation may be written in the final form,

$$TSP(j_{p,i}) \le \phi(j,k)_{prot} \times \left\{ \frac{CCP(m,k)}{CP(m,k) \times RIP(m,q)} \right\}_{Lim} \times D_C \tag{5}$$

where the subscript "prot" denotes the detectors that protect flux shape k. For each flux shape, there must be at least one protecting detector in each safety channel for each shutdown system. The factor "D_C", the detector calibration factor, represents a number of correction factors for CCPs and detector readings.

2.1.2. Probabilistic TSP

To determine the appropriate TSP value which will satisfy the target trip probability (which is typically set as 98%/average), a probabilistic TSP calculation is performed using the ROVER-F code. The details concerning steps for calculating the TSP can be found in [15].

2.2. An Overview of the Genetic Algorithm

The genetic algorithm is one of the optimization methods and its basic concept is derived from the genetic and natural selection in life [16]. To simulate the natural selection process of the Darwinian theory, a candidate solution to an optimization problem is encoded into a representative "digital individual". Inferior individual will be terminated while the superior ones will reproduce their offspring through genetic operations such as the crossover and/or the random mutation. As the evolution process in nature, the simulated evolution process in GA steers the individuals (*i.e.*, candidate solutions) toward favorable region of the design space.

Figure 2 illustrates the GA process from one generation to the next. The first box at the top illustrates the population at "Generation G". The fitness of each individual in this generation is evaluated. From this population of 20 individuals, 10 parents are selected based on its fitness value. In the next step, 10 pairs of crossover process from randomly picked parents are performed, resulting in a set of 20 individuals. A random mutation process is performed in the next box. Based on a predefined mutation rate, *e.g.* 20% in this example, the random mutation is performed. After the mutation process, the population for "Generation G+1" is established, at which point the entire process is repeated.

2.3. An Overview of ADORE Algorithm

The design process using ADORE starts by evaluating detector readings for all flux shapes considered in the analysis. The locations of these candidate detectors have been established prior to the detector layout design process. The locations of the available vertical and horizontal flux detector assemblies dictate where these candidate detectors can be placed. Therefore, for each flux shape, there will be a unique detector reading at each detector location. For example, for a design process where 1500 candidate detectors are considered, each flux shape will have 1500 detector readings.

Since for each flux shape it is true that the detectors with higher readings will trip earlier than those with lower ones, from safety point of view, it is desirable to have these detectors for protecting a particular flux shapes. This is the heart of the ADORE algorithm. Certain numbers of detector which provide the highest readings for a particular flux shape are put in the pool of selected candidate detectors. This process is repeated for all flux shapes and at the end of this process the pool will have all candidate detectors which can be selected to build the ROP system.

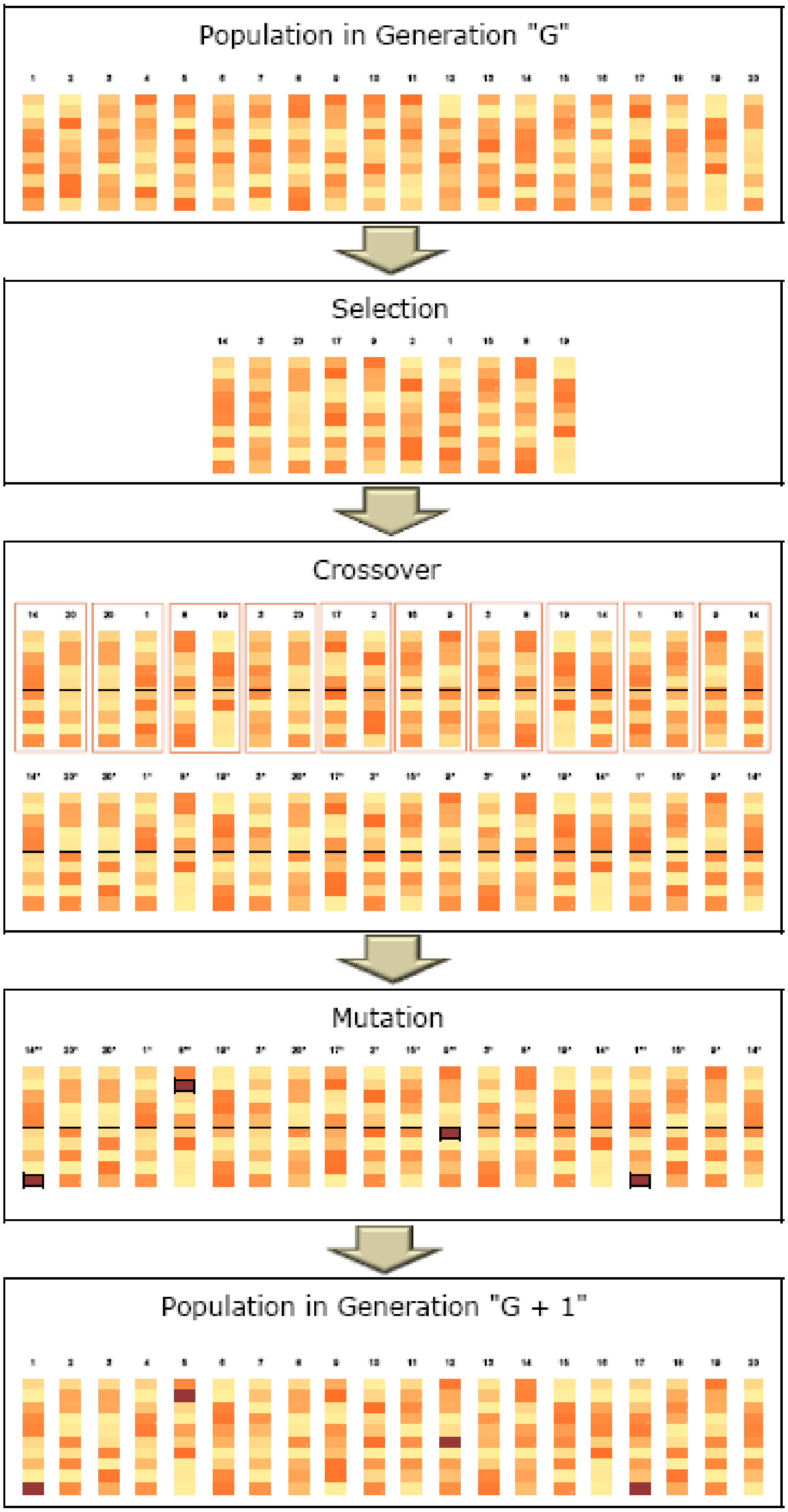

Figure 2. An Example of Creating a Generation within GA Methodology.

The criterion for selecting a detector and putting it in the pool is one of the user-defined parameters in this algorithm. For example, for each flux shape one might pick 10 detectors which have the highest detector readings or one might pick however many detectors which correspond to the top 2% detector reading (with respect to the highest detector reading for that particular flux shape). The resulting pool of candidate detectors will be used to select detectors to be included in the initial generation in the ADORE-GA implementation. The complete description of the ADORE algorithm can be found in [3].

2.4. Implementation of GA in ADORE-GA

The procedures of ROP detector layout optimization using GA are as follows:

a. The initial population of detector layout configurations is randomly generated. Each individual in the population represents a detector layout configuration and is generated by randomly selecting detectors from the pool of candidate detectors described in the previous sub-section. This initial population typically contains hundreds of candidates (*i.e.*, detector layout configurations).
b. Evaluate the TSP for each detector layout configuration using the ROVER-F code. For this implementation, the TSP is the fitness value of a particular configuration.
c. Parent configurations are selected based on their fitness values. During this step, the selection probability is usually proportional to the fitness value, *i.e.*, the higher the fitness value of certain configuration is, the more likely that configuration will be picked as a parent. After the parent configurations are selected, the genetic operations such as the crossover and the random mutations are performed to create an offspring. This process is repeated until the number of offspring meets the size of desired population for a generation.
d. Repeat (b) and (c) until improvement of the fitness value of the best detector layout configuration becomes smaller among several successive generations or until the maximum number of generation is reached. For the current implementation, the latter approach is utilized.

By observing these steps, one can see that the GA is a straight-forward and effective optimization method. However, since there are several user-defined optimization parameters within GA, to ensure that the algorithm works properly, some of these parameters needs to be tuned carefully. This is important in order to avoid "false convergence" during the optimization process. It is already understood that the design space is extremely large. Therefore, to effectively search through this design space, the variation of individual in a population is important. When the variation is too large, the computational time required to obtain a converged solution is high. Conversely, when the variation is too small, although the computational time is usually relatively shorter, the search can be easily trapped in a local optima. The variation of offspring can be controlled by the procedures used for parent selections, crossover, and random mutation. The ideal combination of these procedures is problem dependent. The present paper will only discuss the general implementation of the GA to illustrate that this optimization technique can be successfully used for solving the ROP detector layout optimization problem and will not search for the most effective combination of these procedures.

3. Numerical Results

The genetic algorithm stochastic optimization technique has been implemented in ADORE-GA. The implementation of GA in ADORE-GA has been tested on four different sizes of the ROP systems, namely 68-, 72-, 76-, and 80-detector configurations. The size of the pool of candidate detectors is 503. Based on this information, the search spaces for the detector layout optimization are 2.76E+123[3], 9.29E+128, 2.43E+134, and 4.97E+139 for the 68-, 72-, 76-, and 80-detector configurations, respectively. It is computationally prohibitive to completely search the design space of this size for the optimal solution. Stochastic optimization technique such as GA is the appropriate tool for solving this type of problem to give a quasi optimal solution to the problem.

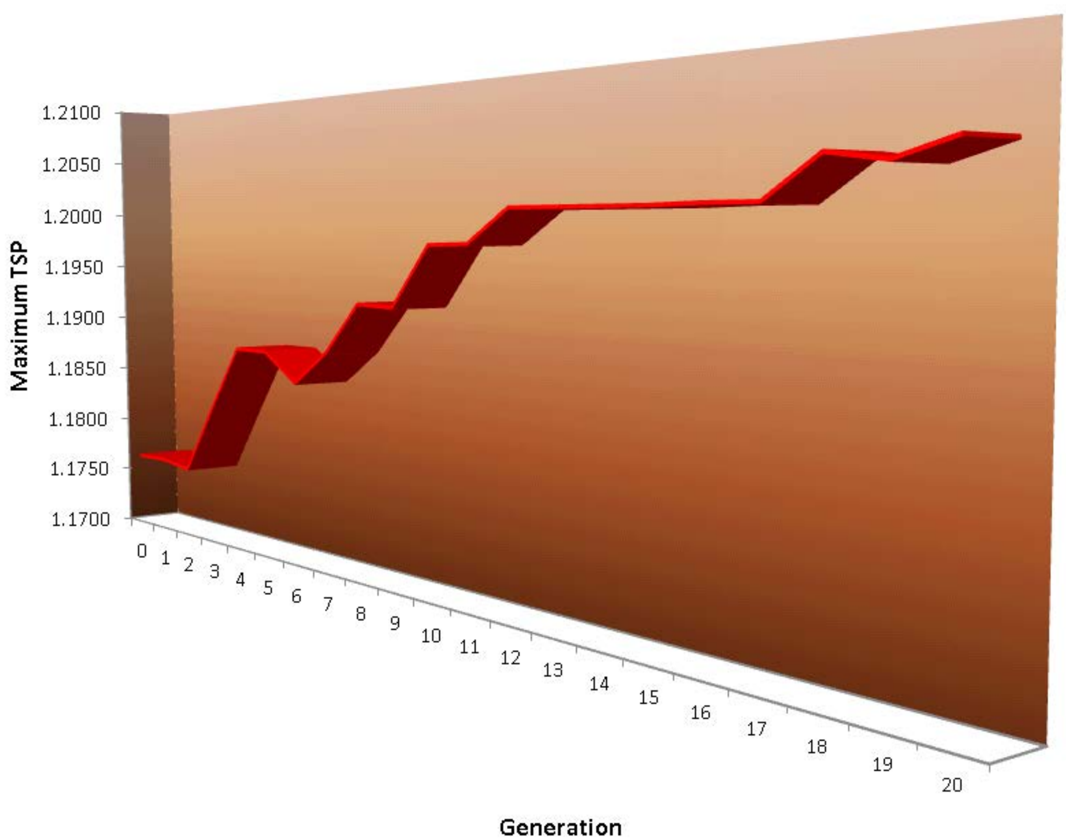

Figure 3 Trip Set Point Evolution During Optimization.

For each configuration size, 15 optimization runs were executed. For this study, the population size per generation is 200 individuals. The mutation rate is 10%. Each run is terminated after 20 generations. It is true that the number of generation used here is considered low. However, the

[3] The search space is calculated as follow: $\left(\frac{503!}{17!486!}\right) \times \left(\frac{486!}{17!469!}\right) \times \left(\frac{469!}{17!452!}\right) \times \left(\frac{452!}{17!435!}\right) = 2.76 \times 10^{123}$

objective of this preliminary study is not to find the ultimate best solution but to demonstrate that GA technique can be adopted for solving the ROP detector layout configuration problems. Figure 3 illustrates the evolution of the quality of the results during the optimization. The x-axis denotes the generation number (where "0" represents the initial population) and the y-axis denotes the maximum TSP (which is a measure of fitness) in each generation. As clearly shown in this figure, the quality of the solution is improved from the beginning to the end of the optimization process. This figure also shows that the improvement is not necessarily monotonously increasing. Sometimes, it is necessary to pass through a generation with slightly lower fitness values before finding a generation which has large number of superior individuals.

The results from testing the ADORE-GA implementation are summarized in Table 1. Presented in this table is the fitness value (*i.e.*, the TSP value) of the best individual found during each optimization run. The variation in the results for each size of the ROP system can also be observed in this table. The average fitness value for each configuration size is also presented. Observing the average fitness value, one can see that on average as the number of detectors is increased, the resulting TSP value also increases.

Table 1 Summary of Trip Set Point Values from Optimization.

Case	**Size of ROP System**			
	68 Detectors	**72 Detectors**	**76 Detectors**	**80 Detectors**
1	1.1952	1.1984	1.1952	1.2062
2	1.1863	1.1941	1.2044	1.2052
3	1.1922	1.1896	1.2022	1.1989
4	1.1943	1.1945	1.2006	1.2014
5	1.1870	1.1956	1.2000	1.2036
6	1.1930	1.1988	1.1981	1.2039
7	1.1937	1.1964	1.2068	1.2037
8	1.1933	1.1970	1.2026	1.2070
9	1.1903	1.1959	1.1984	1.2050
10	1.1899	1.1975	1.1974	1.2050
11	1.1976	1.1951	1.1990	1.1988
12	1.1875	1.1961	1.2013	1.2037
13	1.1922	1.1940	1.2017	1.2052
14	1.1933	1.1988	1.1993	1.2028
15	1.1953	1.1932	1.1992	1.2059
Average	**1.1921**	**1.1957**	**1.2004**	**1.2038**

4. Conclusion

A variant of the ADORE algorithm for optimizing the detector layout configuration for the ROP system in CANDU reactors has been introduced in this paper. The GA stochastic optimization technique has been implemented within the ADORE algorithm. The implementation had been evaluated by examining its performance in trying to solve detector layout configuration problems for four different sizes of ROP system. Considering the fact that limited number of generations has been evaluated in each optimization run, the resulting TSP values from the numerical experiments are acceptable.

5. References

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