Applying Genetic Algorithms to the Data Traffic Scheduling and Performance Analysis of a Long-Term Evolution System

Hsien-Wei Tseng
Dept. of Computer and Communication Engineering
De Lin Institute of Technology
Tucheng District, New Taipei City 23654, Taiwan
hsienwei.tseng@gmail.com

Yang-Han Lee
Department of Electrical Engineering
Tamkang University
Tamsui District, New Taipei City 25137, Taiwan
yhleepp@gmail.com

Wei-Chen Lee
Department of Electrical Engineering
Tamkang University
Tamsui District, New Taipei City 25137, Taiwan
s8714066@gmail.com

Yih-Guang Jan
Department of Electrical Engineering
Tamkang University
Tamsui District, New Taipei City 25137, Taiwan
yihjan@yahoo.com

Chorng-Ren Sheu
V200, Information & Communications Research Laboratories, Industrial Technology Research Institute
Rm. 255, Bldg. 11, No. 195, Sec. 4, Chung Hsing Rd., Chutung, Hsinchu, 31040, Taiwan, R.O.C.
crsheu@itri.org.tw

Abstract—**This study developed a superior transmission resource allocation method using genetic algorithms. The convergence properties of genetic algorithms were employed to increase the transmission resource use efficiency of a base station, allowing users to access wider bandwidths and improving the system throughput and packet service rates of a multicarrier operation. This study also determined the genetic algorithm convergence time and found that the convergence time required for actual calculation was significantly less than one radio frame duration. Finally, the resource allocation results were simulated with and without the genetic algorithm to compare the performance differences.**

Keywords- Genetic algorithm; resource allocation; multicarrier operation

I. INTRODUCTION

With increasing demand for personal and corporate data transmission and communication quality, communications industries and researchers continue to test new communications technologies and develop mature handling hardware to meet this demand. The International Telecommunication Union (ITU) has recently begun planning and developing fourth-generation mobile communication technology standards (IMT-Advanced) based on their previous experience standardizing third-generation mobile communication technology. The IEEE 802.16 m physical layer transmission technology developed by the Institute of Electrical and Electronics Engineers (IEEE) contains orthogonal frequency-division multiple access (OFDMA) technology. The wireless transmission technology resources available to users comprise frequency and time-dimension levels. Therefore, appropriately allocating the frequency and time of transmission resources has become a critical issue. This study employs genetic algorithms to determine the user transmission resource allocation, and uses genetic algorithm resource allocation for multicarrier operation cases.

This study is arranged as follows: In Chapter 2, a long-term evolution (LTE) system [1-8] with a radio frame format and a resource-planning unit is introduced. In Chapter 3, the genetic algorithm [9-13], how the genetic algorithm resource allocation method is employed in this study, and the application of genetic algorithm resource allocation using the multicarrier method is explained. In Chapters 4 and 5 the system resource allocation simulation results are analyzed, and the conclusion is presented in Chapter 6.

II. INTRODUCTION OF THE LONG-TERM EVOLUTION SYSTEM

The LTE system is a set of system specifications developed by the Third-Generation Partnership Project (3GPP) in 2004. The 3GPP abandoned the code division multiple access (CDMA) technique used in third-generation mobile communication systems when developing this system standard. Instead, OFDMA was employed as the multiple access downlink technology. SC-FDMA, which has a lower peak-to-average power ratio (PAPR) compared to OFDMA, was employed for the uplink. The bands used by the LTE system range between 1.4 MHz and 20 MHz [8]; the LTE system antenna was designed to support multi-input multi-output (MIMO); and the LTE system supports the time division duplex (TDD), frequency division duplexing (FDD), and half-duplex frequency division duplex (H-FDD) modes.

The LTE TDD radio frame structure is shown in Fig. 1. The length of one radio frame was 10 ms. When one radio frame was divided into 10 subframes, the length of each subframe was 1 ms. Regarding the subframes, one or two can be used as special subframes, as shown in the slanted line area of Fig. 1. The remaining subframes can then be divided into two slots, where each slot is 0.5 ms in length.

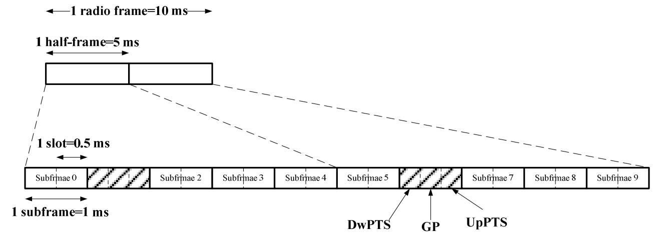

Figure 1. The TDD Radio Frame of the LTE System

The LTE FDD radio frame structure is shown in Fig. 2. One 10-ms radio frame was divided into 10 1-ms subframes, and each subframe was divided into two 0.5-ms slots. In the H-FDD mode, the user device cannot send and receive simultaneously. However, the FDD mode does not have this restriction.

Regarding the LTE system specifications, one resource block is set to use 12 frequency subcarriers, and the allocated time equals one symbol slot. Based on the various CP settings, the length of time for the resource block is seven symbols when normal CP is used and six symbols when extended CP is used.

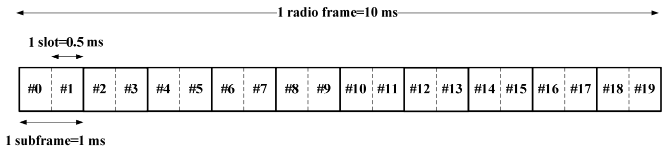

Figure 2. LTE FDD Radio Frame Structure

III. INTRODUCTION OF GENETIC ALGORITHM

Mutation is achieved by manipulating single chromosomes. This prevents the genetic algorithms from falling into optimal solution regions during computation; however, excessively high mutation rates can hinder the identification of optimal solutions. Fig. 3 shows a binary bit chromosome mutation operation type. Selections are made based on each individual's fitness value in the fitness value calculation group. Chromosomes with a high fitness value are more likely to be selected as parents of the next generation. The following two methods are generally employed for selection: roulette wheel selection and tournament selection. The roulette wheel selection method is similar to Russian roulette, as shown in Fig. 4. Chromosomes with greater fitness values occupy a larger block and, thus, have a greater probability of being selected for replication. Under the tournament selection method, mating for the mutant offspring is conducted randomly (by one or more pairs), with the best offspring selected and copied into the new parent.

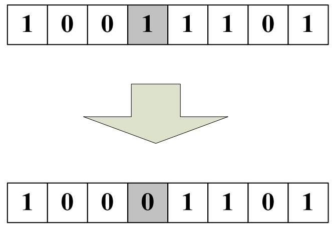

Figure 3. Single-Point Mutation of Binary Chromosomes

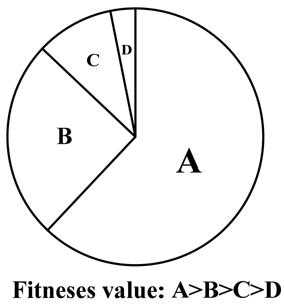

Figure 4. Roulette Selection Method

Fig. 5 shows that User 1 was selected for this study. The location of Chromosome 1 was the first frequency band of the first subframe. The location of Chromosome 2 was the first frequency band of the fifth subframe. Subsequently, user data was exchanged for the chromosomes in these two locations, thereby completing the mating of these two chromosomes.

The steps of the mutation process are shown in Fig. 6. A single chromosome was used for mutation. The steps of the mutation process designed by this study are similar to those of the mating process. First, one user is randomly selected from any chromosome. Then, the location of the user data is randomly moved, although the user's original data distribution shape is maintained (the same number of subframes and frequency).

Because the genetic algorithm must determine the goodness-of-fit of the chromosome, the fitness function was defined to establish the proportion of offspring that must be copied during the selection step. The format of the fitness function shown in Fig. 7 was defined to enable more compact allocation of user data in the radio frame. The remaining resource unit/resource block pairs (Remaining RU/RBPs) were used to determine the goodness-of-fit of the chromosome within the group. The more Remaining RU/RBPs, the higher the chromosome quality. The Remaining RU/RBPs were identified using the back-calculation method, beginning at the bottommost resource unit/resource block (RU/RB) until the user's data was encountered.

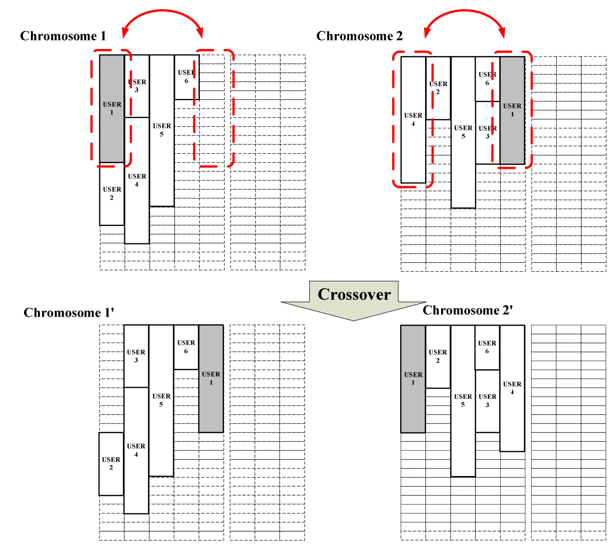

Figure 5. Diagram of the Mating Process for Resource Allocation

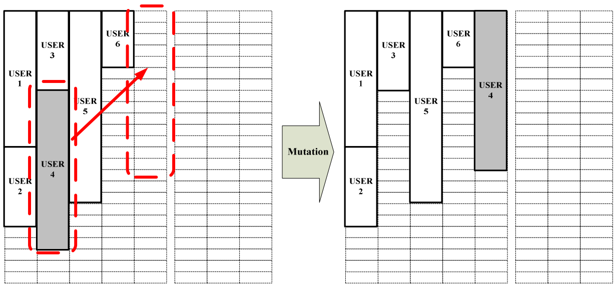

Figure 6. Diagram of the Mutation Process for Resource Allocation

When chromosomes are generated, the only difference between the chromosomes should be the allocated location of each user's resources, which enables mating and mutation to be conducted successfully. By repeating numerous genetic algorithm calculations, one or several solutions can be obtained, which further compact the user data in the radio frame. After completing this step, this radio frame can be used by other users for resource allocation. This procedure is shown in Fig. 8.

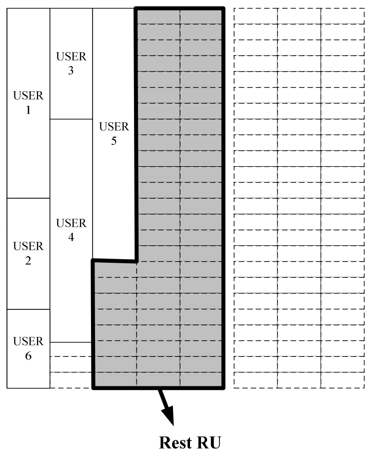

Figure 7. The Fitness Function of Resource Allocation – Remaining RU/RBPs

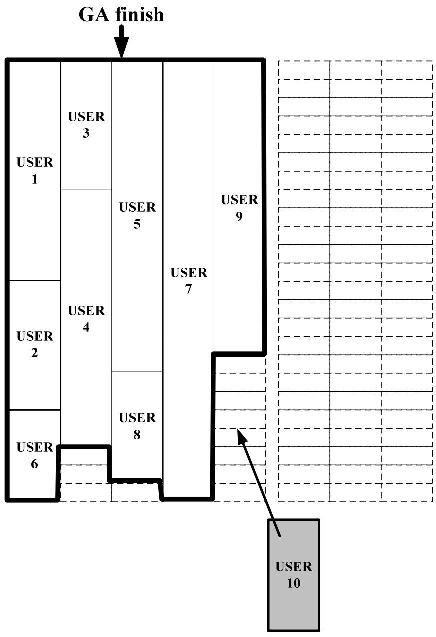

Figure 8. The Inclusion of Additional User Data in Resource Allocation after Genetic Algorithm Calculation

IV. GENETIC ALGORITHM RESOURCE ALLOCATION USING THE MULTICARRIER METHOD

Under the multicarrier method, data in the LTE system is allocated from the upper layer to the physical layers of various carriers. User data is assigned to an appropriate carrier before the data allocation step is conducted. The dimensions of the chromosomes were increased from two dimensions (time and frequency) to three dimensions (time, frequency, and carrier), as shown in Fig. 9. The mating and mutation of the multicarrier chromosome are shown in Figs. 10 and 11, respectively. Subsequently, the location of the user data exchange was no longer limited to a single carrier. A genetic algorithm was used to determine suitable times, frequencies, and carrier locations for user data. The fitness value of the multicarrier chromosome was the total Remaining RU/RBPs for each carrier, as shown in Fig. 12.

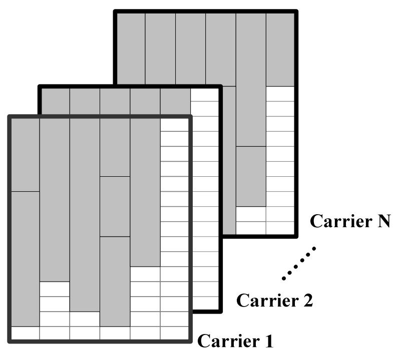

Figure 9. Multicarrier Chromosome Form

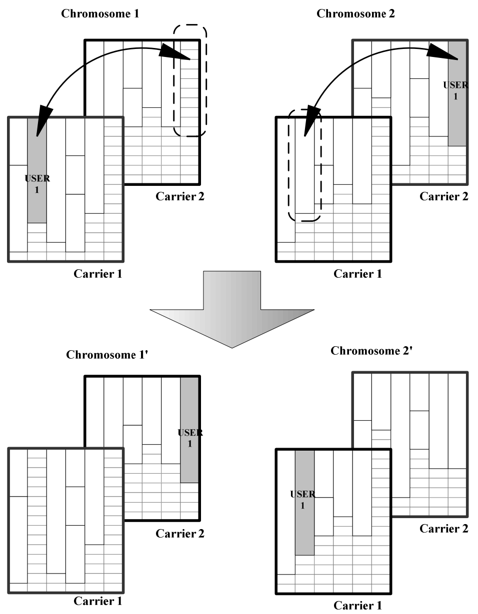

Figure 10. Multicarrier Chromosome Mating

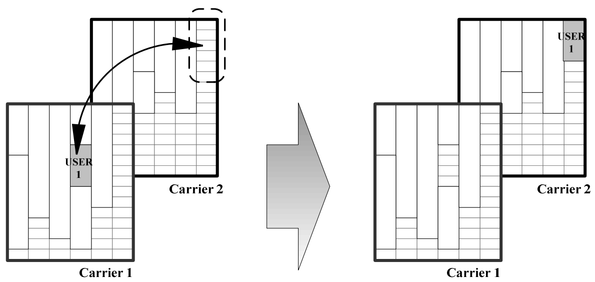

Figure 11. Multicarrier Chromosome Mutation

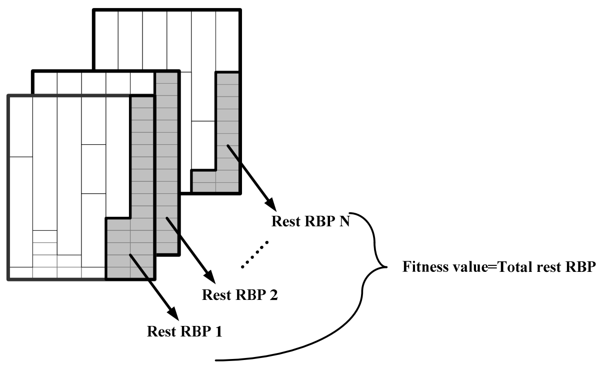

Figure 12. Fitness Value of the Multicarrier Chromosome

V. SYSTEM PERFORMANCE SIMULATION RESULTS AND ANALYSIS

This study explored how the genetic algorithm transmission resource allocation method affects system performance. The system performance and genetic algorithm convergence speed with varying numbers of carriers were compared.

A. *LTE System Performance Simulation*

This study compared the throughput and packet service rate differences under single-carrier resource allocation, both using and not using a genetic algorithm. Only downlink resource allocation was examined in this study. Table I shows the service type, data rate, and service probability values used for the simulation. Tables II and III are the LTE parameters under the TDD and FDD modes, respectively. The results indicated that, because the genetic algorithm method uses transmission resources more efficiently during resource allocation, its throughput and packet service rates are superior to those of the random method.

TABLE I. SERVICE TYPE AND DATA TRANSMISSION RATIO

Service	VOIP	Video Stream	FTP(DL)	HTTP
Data rate (kbps)	64	256	2000	128
Ratio (%)	50	20	10	20

TABLE II. LTE AND TDD SIMULATION PARAMETERS

LTE TDD Simulation Parameters	
Simulation time	20 ms
Bandwidth	10 MHz
Used subcarriers	600
Subcarrier spacing	15 kHz
Duplex	TDD
DL subframe	6
Modulation	QPSK
Coding rate	1/3
Pilot pattern	2 antenna port
Cyclic prefix	Normal

TABLE III. LTE AND FDD SIMULATION PARAMETERS

LTE FDD Simulation Parameters	
Simulation time	20 ms
Bandwidth	10 MHz for DL
Used subcarriers	600
Subcarrier spacing	15 kHz
Duplex	FDD
DL subframe	10
Modulation	QPSK
Coding rate	1/3
Pilot pattern	2 antenna port
Cyclic prefix	Normal

Figs. 13 to 14 show the simulation results for the LTE FDD modes when a genetic algorithm was used for resource allocation and the number of carriers were 1, 2, and 4. The higher the number of usable carriers, the better the throughput and packet service rate performance.

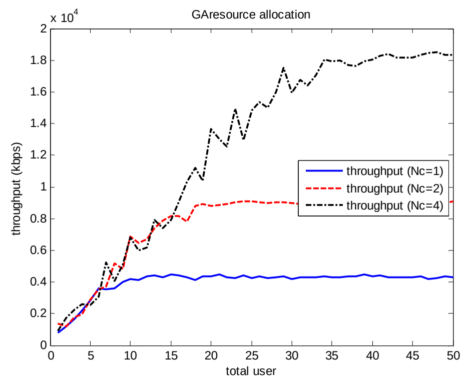

Figure 13. LTE FDD Throughput With 1, 2, and 4 Carriers

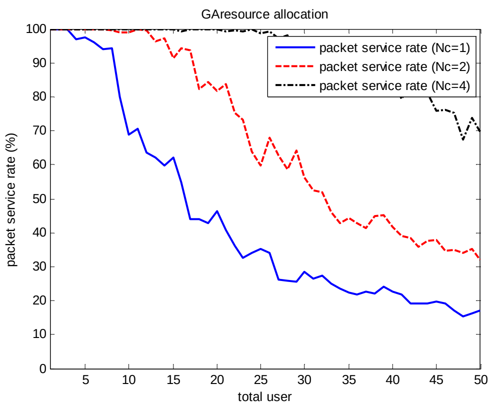

Figure 14. LTE FDD Packet Service Rate With 1, 2, and 4 Carriers

B. *Genetic Algorithm Convergence Analysis*

Before comparing the convergence under varying numbers of carriers, the fitness values (Remaining RU/RBPs) defined previously were revised to facilitate comparison. First, the average Remaining RU/RBPs per carrier were defined as follows:

$$fit_{avg} = fit / N_c \tag{1}$$

where

fit is the total Remaining RU/RBPs of all carriers and N_c is the number of carriers.

Then, fit_{avg} was used to normalize the average Remaining RUs per carrier, as shown below.

$$fit_{normal} = 100\% \times (fit_{avg} / convg(fit_{avg})) \tag{2}$$

where $convg(fit_{avg})$ is fit_{avg} after convergence.

Figs. 15 and 16 are LTE TDD and LTE FDD convenience speed comparison charts with varying carrier numbers and 50 users. The horizontal axis is the variable of the genetic algorithm, and the vertical axis is fit_{normal}. According to literature references [15], the average time required for the actual hardware test to calculate 20 generations using a genetic algorithm is 22.4 ms, with an average of 1.12 ms per generation. This value was used as the basis for estimating the hardware calculation time of the genetic algorithm resource allocation method proposed in this study. Tables III and IV list the average convergence variables and the hardware calculation time for the TDD and FDD modes, when the ILTE radio frame length was 5 ms, with varying carrier numbers and 50 users. The convergence variable was defined as the minimum variable fit requirement of $fit_{normal} \geq 90\% \times convg(fit_{avg})$. Tables IV and V show that the calculated convergence time required for actual computation was significantly less than the frame length, and as the number of carriers increase, the convergence time also increases. Regarding the duplex mode of the same system, FDD provides more arrangeable RU/RBP than that of TDD; thus, FDD has a slower convergence speed compared to TDD.

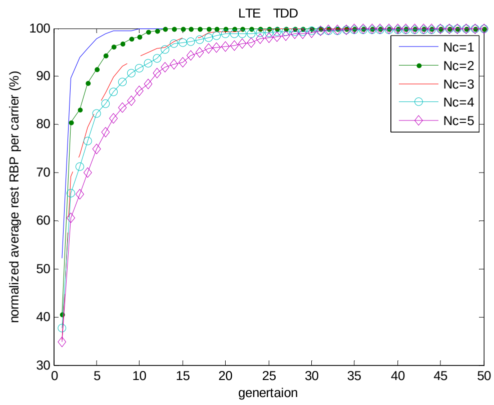

Figure 15. LTE TDD Multicarrier Convergence Rate Comparison

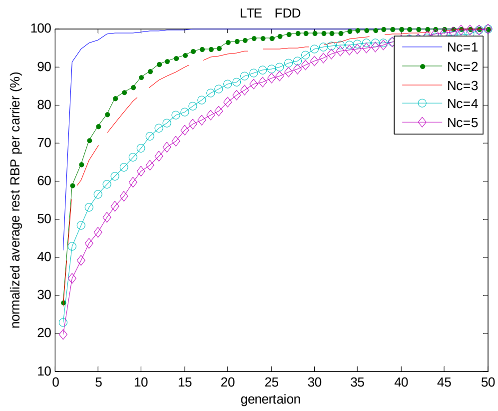

Figure 16. Comparison of LTE FDD Multicarrier Convergence Rates

TABLE IV. LTE TDD MULTICARRIER AVERAGE CONVERGENCE VARIABLES AND ESTIMATED CONVERGENCE TIME

Radio Frame Length (ms)		**Nc=1**	**Nc=2**	**Nc=3**	**Nc=4**	**Nc=5**
10	***Average Convergence Variables (Ng)***	2.9	4.55	7	8.45	11.4
	Estimated Convergence Time (Ng*1.12us)	3.248	5.096	7.84	9.464	12.768

TABLE V. LTE FDD MULTICARRIER AVERAGE CONVERGENCE VARIABLES AND ESTIMATED CONVERGENCE TIME

Radio Frame Length (ms)		**Nc=1**	**Nc=2**	**Nc=3**	**Nc=4**	**Nc=5**
10	***Average Convergence Variables (Ng)***	2.7	11.3	14.9	25.05	26.05

	Estimated Convergence Time (Ng*1.12us)	3.024	12.656	16.688	28.056	29.176

VI. CONCLUSION

This study used genetic algorithm convergence to identify superior transmission resource allocation methods that enable more efficient use of transmission resources and enhance the system throughput and packet service rate. Besides single-carrier resource allocation, the genetic algorithm resource allocation method was applied to multicarrier operations, enabling base stations to use transmission resources more effectively when providing larger bandwidths to users. Finally, through calculations, this study found that the genetic algorithm convergence time is significant less than one radio frame duration.

Tables VI and VII show comparisons of the performance of LTE TDD and LTE FDD systems with varying numbers of carriers and 50 users. These tables indicated that the larger the carrier number, the better the throughput and packet service rates. In the TDD mode, the four-carrier packet service rate was 30.08%, which is higher than the one-carrier packet service rate of 9.423%. In the FDD mode, the four-carrier packet service rate was 69.07%, which is higher than the one-carrier packet service rate of 17.15%. Considering that the downlink bandwidth of the TDD and FDD modes is the same under the same system, the performance of the TDD mode is slightly worse than that of the FDD mode, although the high-carrier packet service rate is significantly improved.

TABLE VI. COMPARISON OF LTE SYSTEM PERFORMANCE WITH VARIOUS NUMBERS OF CARRIERS (TDD MODE, 50 USERS)

Carrier number	**Throughput (kbps)**	**Packet service rate (%)**	**Average convergence variable**
Nc = 1	2645	9.423	2.9
Nc = 2	5423	20.09	4.55
Nc = 4	11160	38.08	8.45

TABLE VII. COMPARISON OF LTE SYSTEM PERFORMANCE WITH VARIOUS NUMBERS OF CARRIERS (FDD MODE, 50 USERS)

Carrier number	**Throughput (kbps)**	**Packet service rate (%)**	**Average convergence variable**
Nc = 1	4271	17.15	2.7
Nc = 2	9094	32.13	11.3
Nc = 4	18330	69.7	25.05

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