

Optimization of Electrical Energy Consumption and Level Reliability of Water Supply System

Mohd Ismail Jusoh^a, Folorunso Taliha Abiodun^b, Fatimah Sham Ismail^{c*}, Sohailah Shafie^c

^aDepartment of Electronic Engineering, MARA-Japan Industrial Institute Berang, Selangor, Malaysia

^bDepartment of Computer Engineering, Federal University of Technology Minna, Nigeria

^cCenter for Artificial intelligence and Robotics (CAIRO), Universiti Teknologi Malaysia, Jalan Semarak, Kuala Lumpur, Malaysia

*Corresponding author: fatimahs@fke.utm.my

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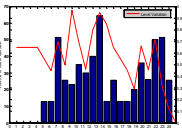
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Graphical abstract



Abstract

Generally, high operational cost is associated with all water supply system. This is as a result of the high amount of electric energy consumption ascribed to the system due to its components. The water supply system of the Mara-Japan Industrial Institute (MJII), Beranang, Selangor is one of such system that suffers this challenge of high operational cost. In this paper we have applied the use of an Adaptive Weighted Sum Genetic Algorithm to optimize the system operations such that it minimizes the high energy consumption as well as ensuring the overall reliability of the water level in the reservoir. The results obtained from the optimized model of the system show a promising and a significant reduction to the tune of 34.97% in the amount of energy consumed as compared with that of normal operations.

Keywords: Scheduling optimization; adaptive weighted sum genetic algorithm; water supply system

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1.0 INTRODUCTION

Water Supply system plays an important role in an urban infrastructure, as it is responsible for the effective supply and distribution of water from one point to another till it gets to the end users. Generally, the system design is such that it satisfies the end user demand requirements as well as some operational objectives aimed at attaining and satisfying some performance level in the system. As the end user demand increases the over complexity of the system increases making the system a complex one to deal with [1].

The conventional water supply system (WSS) is equipped with numerous high cost and high energy consuming components such as the heavy duty electric pumps, elevated tanks different and varying size of pipeline network and a times a treatment facility. These pumps have either the same sizes or otherwise depending on their locations or functions within the system and they are used to convey water to and fro various location within the station and down to the end user.

Characteristically, the water supply system has a high operational cost associated with it as a result of the operations of the high energy consuming components in it. Specifically, these electric pumps consumes significantly high amount of energy as a result of the nature of work they do, their power rating and coupled with the electric tariff than any other component of the water supply system [1, 2]. According to research, these pumps accounts for about 43% of the entire energy of the station, which

cumulatively results into a high amount of energy consumed. Furthermore, about €700 Million is been expended on pumping activity of the water supply system in the United Kingdom, about 30 to 50 percentage of the overall expenditure of the water supply system in China is paid on electric energy consumption of the components used for pumping of the water [3, 4].

Thus, in order to make the water supply system more economically reliable, there is a need for the optimization of the system in terms of reduction or minimization of the operational cost of the system which could be in terms of the energy cost, treatment and maintenance costs and still been able to satisfy the demand requirements of the consumers. In the optimization of the system, numerous approaches have been employed such as pumping of less water, lowering the head against which water is delivered and scheduling the operations of the pump to concentrate more pumping activity to concentrate more during less expensive tariff period.

Of all the aforementioned approaches, the scheduling operations of the pumps has proven to be the most reliable and viable means of achieving a reduced operational cost without necessarily making changes to the system infrastructure [1]. Pump scheduling involves the process of selecting the right combination set of pumps within the system to operate at a specified time in order to meet the desired objective. Hence, a pump schedule is the set of all pump combinations chosen for all time intervals of within the scheduling horizon which must satisfy particular objective (such as energy and or maintenance cost) for

which it was created while fulfilling the physical and system requirements [1, 4].

In optimizing the pump schedule emphasizes is most often laid on the need to minimize the cost of the electric energy [4-6] alongside other objectives such as maintenance cost [4], maximum peak [4] and environment protection [2]. The energy cost composes of the demand charge (KW) which price is fixed over a period of time and the energy consumption charge (KW-h) whose price varies depending on the time of the day divided into the peak and off-peak period. The maintenance cost is associated with cost of maintaining the wear and tear developed as result of switching the pumps on/off.

Various classical techniques of optimization such as linear programming [7, 8], non-linear programming [9, 10] and dynamic programming [11, 12] have been applied to the problem of creating optimal pump schedule for the water supply system. However, these techniques may not be suitable for all types of system and also as the complexity and constraints of the system increases, applying these techniques becomes challenging and difficult. Thus, with the advancement in computational intelligence specifically in the field Genetic Algorithm (GA), its use to solving the problem of creating optimal pump scheduling for the water supply system and also resolving the challenges arising from the use of the classical optimization techniques as been on the increase.

In this paper, we adopt a special type of Genetic Algorithm based on the weighted sum approach known as the Adaptive Weighted Sum Genetic Algorithm (AWGA) [13] to create an optimal pump schedule for Mara-Japan Industrial Institute (MJII) Selangor water supply station aimed at minimizing the operational cost in terms of the energy consumption and also maintaining a reliable reservoir water level thus satisfying the system constraints. The Adaptive Weighted sum Genetic Algorithm (AWGA) is based on the weighted sum approach of the Genetic Algorithm and it is designed such that the information of the fitness functions is used to determine and readjust the weights on every generation of the Genetic Algorithm process. The remaining part of this work is divided into four (4) sections. Section II focuses on the description of the case study system and its modeling. The detailed description of the proposed AWGA technique is presented in Section 2. Section 3 discusses the results obtained and Section 4 concludes the paper.

2.0 METHODOLOGY

2.1 System Model

MJII pumping stations consist of two pumps that work in parallel to deliver water into an elevated reservoir, from where it supplies the end user consumers by gravity. Figure 1, shows an approximated model of the MJII water supply system where P_1 and P_2 are the two operational pumps. The pumps works operates based on sequential command received from control consul inside the control room of the station.

The system model is approximated such that the pump characteristic parameters such as the power rating and flow rates are assumed to be fixed over the scheduling period. While the reservoir is defined to have an initial level h_{int} that corresponds to the start level of water in the reservoir and must be recovered at the end of the optimization period. The h_{max} and h_{min} levels corresponding to the maximum and minimum level respectively, above and below which the water level in the reservoir must not exceed at any point in time during the optimization period. The goal is to maintain the level between the minimum and maximum level by putting the initial level h_{int} into consideration.

Figure 2 shows the water demand profile per hour for a day. Data is obtained through statistical study of the water consumption level of the MJII over a period of time and the obtained average is as presented as the demand profile.

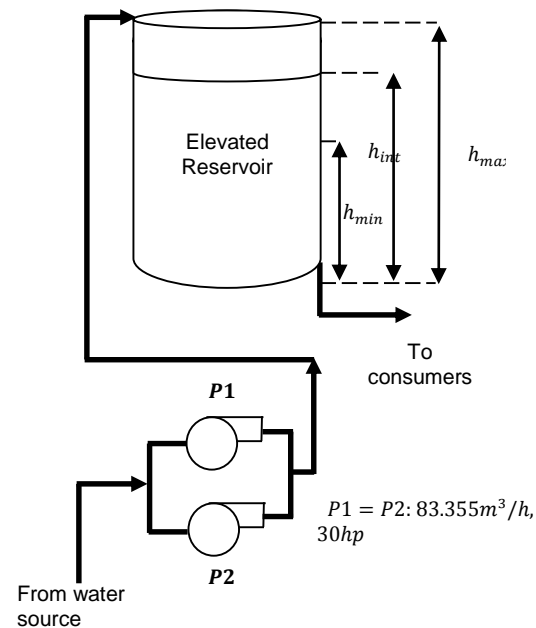


Figure 1 System Model

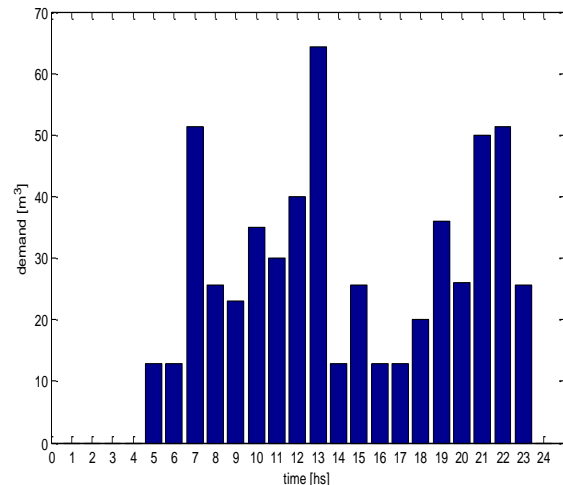


Figure 2 The water demand profile

2.1.1 Electrical Energy Cost

The electrical energy cost of the water supply system is the cost of electric energy consumed by the operating pumps in the system influenced by power rating of the pumps and also electric charge tariff plan by the energy utility company. The consideration of the demand charge (KW) is ignored in this study as it does not significantly increases or reduces the cost of energy due to the fact that it is fixed over a long period. Hence only the consumption charge (KW-h) is considered which is based on the tariff plan. The electric charge tariff varies between off-peak and peak period based on the following structure:

- Low cost: (C_{el}): from 0:00 to 08:00 hour and from 22:00 to 24:00 hour (20% Discount of Normal Electric tariff rate).
- High cost: (C_{eh}): from 08:00 to 22:00 hour (Normal Electric Tariff Rate).

The mathematical expression of electric energy cost E_c is defined by Equation (1) [13].

$$E_c = C_{el} \sum_{j=1}^8 e(p_j) + C_{eh} \sum_{j=9}^{22} e(p_j) + C_{el} \sum_{j=23}^{24} e(p_j) \quad (1)$$

Where

C_{el} : Off-peak tariff price

C_{eh} : Peak tariff price

j : Time interval

p_j : Pump combination at interval j .

$e(p_j)$: Electrical energy consumed

2.1.2 Model Constraints and Assumptions

The maximum and minimum levels of the water in elevated reservoir are considered as the model constraints; if the level of the water in the elevated reservoir exceeds the maximum level h_{max} , wastage of resources would occur. If the level of the water exceeds the minimum level h_{min} , it satisfies the emergency requirement. The minimum and maximum constraint is defined by Equation (2) [13].

$$h_{min} \leq h_i \leq h_{max} \quad (2)$$

where

$$h_i = h_{i-1} + \frac{[Q_i - WD_i]}{s} \quad (3)$$

h_{min} Minimum water level

h_{max} Maximum water level

h_i Level at interval i

S Elevated reservoir surface

Q_i Quantity of water pumped at time interval i

WD_i Water demand at time interval i

These are the assumptions of the model constraints to be considered:

- the amount of water source supplies enough water at any time and without additional costs;
- the maximum and minimum pressure constraints in the pipeline are always fulfilled, no matter what level is kept in the reservoir;
- valves in the system model are not considered;

2.2 The Adaptive Weighted Sum Genetic Algorithm

Genetic Algorithms (GA) are adaptive heuristic search evolutionary based algorithms that uses the concept of selection and genetic to search for possible solutions to a problem within a defined criterion space. The Adaptive Weighted sum Genetic Algorithm (AWGA) is one of such algorithms and based on the weighted sum approach of the GA.

Basically, in the AWGA each objective function in the problem is allocated a weight be it a single objective or multi-

objective problems. The advantage of the AWGA lies in the adaptive nature of selecting its weights as compared to other types of weighted sum GA. The weights multipliers are selected using the maximum and minimum fitness values of the objective functions and making it liable to change on each of the GA iteration. By so doing no single objective function takes dominance over the other in their combination to form a Multi-objective function. Thus, this makes the AWGA more robust and adaptive.

The process of Adoption of the AWGA for creating the optimal pump schedule for MARA-Japan Industrial Institute starts with initialization stage as shown in the AWGA implementation flowchart in Figure 3. At this stage all the parameters of the water supply system such as the water demand profile, the pump characteristics of the system, the electric tariff plan as well as the constraints that needs to be satisfied are defined. Also, those that are specified at this stage are the parameters of the Genetic Algorithm itself, which includes the number of generations, the number of chromosomes in the initial population, the rates of mutation, crossover and selection.

To generate the chromosomes, which form the initial population to the GA, it is required that the decision variable is encoded in any of the available techniques to represent the chromosomes of the Algorithm. The binary coding technique was adopted to encode the decision variable (the pump), with each pump represented by bit of '1' pump is on or '0' pump is off in a string of bits at each time interval. The number of bits required to represent a chromosome is determined by multiplying the number of decision variables by the total number of intervals in the optimization period. An optimization period of a day was chosen, with an interval of 1 hour resulting in a total interval of 24, hence the number of bits *numbits* required to represent the chromosomes is given by Equation (4).

$$numbits = numvar \times n \text{ interval} \quad (4)$$

Where *numvar* is the number of decision variables (the pumps in the system), *n* is the number of interval in the optimization period.

This system have 2 pumps hence a string of $2 \times 24 = 48bits$ are used to encode a possible solution.

In this proposed algorithm, the chromosomes are individually created and checked if it satisfies the constraint of the system, it is passed to the initial population or else it is rejected. This process is repeated until the required number chromosomes specified in the initialization stage are met.

The adaptive weights are formed in order to evaluate the fitness values from the individual objective function. The adaptive weight relies heavily on the fitness values of the chromosomes in the current generation for its determination and readjustment on every generation or iteration of the process. This methodology also ensures that no fitness function completely dominates or takes control of the other in their combination to form the total weighted sum objective function.

The genetic operators refer to the selection, crossover and mutation. The first operator to be initialized is the selection operation. This is carried out by selecting the best and the most suitable chromosomes based on their fitness values to be seeded to the next iteration of the genetic process and also to go into the crossover and mutation process. After the mutation process is completed, there is a high probability that some of the offspring produced violates the constraint.

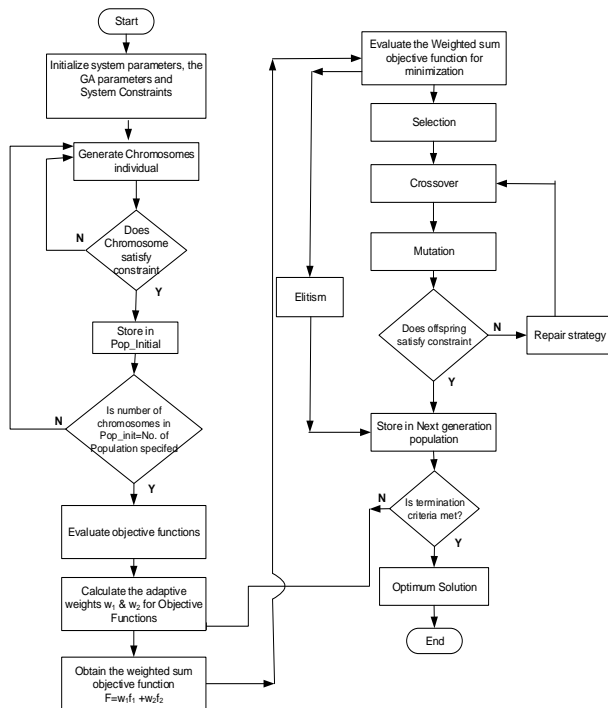


Figure 3 Flowchart of the Adaptive weighted sum GA

A repair strategy [13] is introduced as a means of handling the constraint violation and its steps are as shown in Table 1. The Elitism is another mechanism used to ensure the safety of the best and most feasible solutions of a generation and they are seeded to the next generation. In this work the best two off springs in every generation of the GA is seeded to the next generation.

Table 1 The repair strategy table

Step I: Initialize the repair counter
Step II: Discard offspring
Step III: Repeat the crossover process with the same parents and then the mutation.
Step IV: Check the newly created offspring for the constraint violation
Step V: If the constraint is satisfied move the offspring to next generation population Step 9.
Step VI: If the constraint is violated, Increase the repair counters and go to step 3
Step VII: If the repair counters \geq stop condition, initiate the repair strategy
Step VIII: Initiate Repair strategy
Search for the interval with the violation
If overflow switch OFF one or more pumps until constraint is satisfied
If underflow switch ON one or more pumps until constraint is satisfied
Move offspring to next Generation population
Step IX: Next Generation population

3.0 RESULTS AND DISCUSSIONS

To obtain a reliable and sustainable result using Genetic Algorithm, it is required that the parameters of the GA are properly and carefully selected. The population size is one of such parameters; in determining it four different population sizes were

used to obtain the most effective as shown in Figure 3. With small population size ($C=50$) the algorithm took longer time to converge. The convergence time of the algorithm improves when population size (C) is increased from 100, 200 and 250. In it can be seen that the convergence of $C=200$ is faster than the others. Hence, $C=200$ is selected in this study.

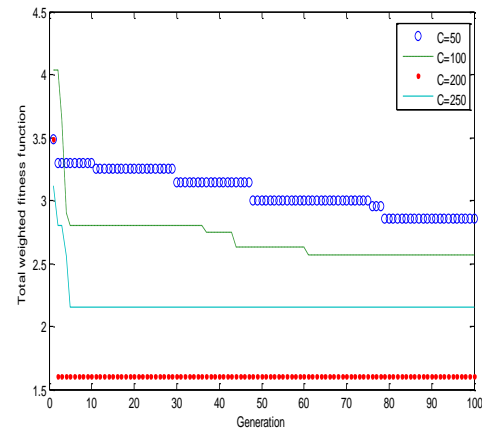


Figure 4 Convergence with difference population size

The next step is to obtain the desirable required number of generations; this is to ensure that the GA is not terminated prematurely before the optimal solution is arrived at. Presented in Figure 4 is the performance of the AWGA when subjected to various generations (500, 2000 and 3000) to obtain the optimal generation.

All the tests show that the algorithm converged for generation 500, 2000 and 3000 are at 5th iteration, 2nd iteration and 6th iteration respectively. The best result obtained which gives the minimum electrical energy cost is when the number of generation is 2000. Hence it is selected for this study.

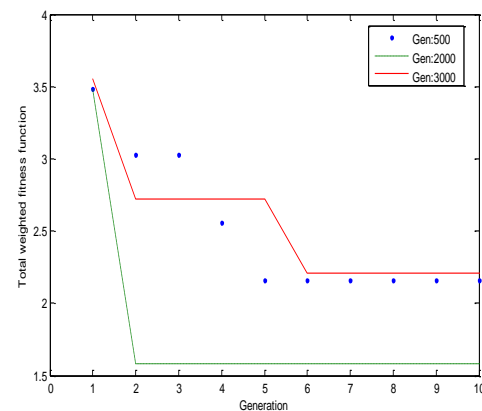


Figure 5 Performance with 500, 2000 & 3000 generation

Furthermore, the remaining parameter such as the crossover rate and mutation rate were stochastically selected based on guidelines [15], for large population such 100, crossover rate, $P_c=0.6$ and mutation rate, $P_m=0.001$. Figures 5 and 6 show the results obtained when the number of generations were retained. Although when the value of population changed to $C=200$, $P_c=0.4$ and $P_m=0.05$, the electrical energy cost can be reduce less than the result are obtained when $C=100$. As a result the value of $C=200$ is used in this study.

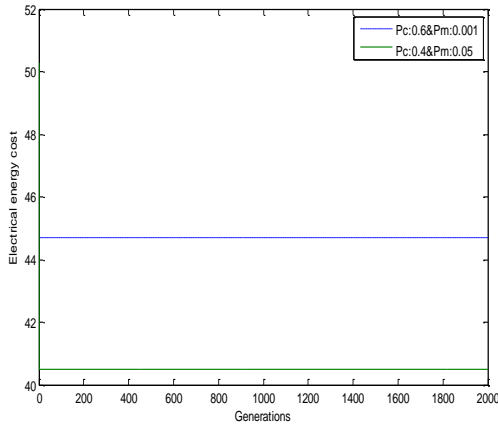


Figure 6 The electrical energy cost for C=100

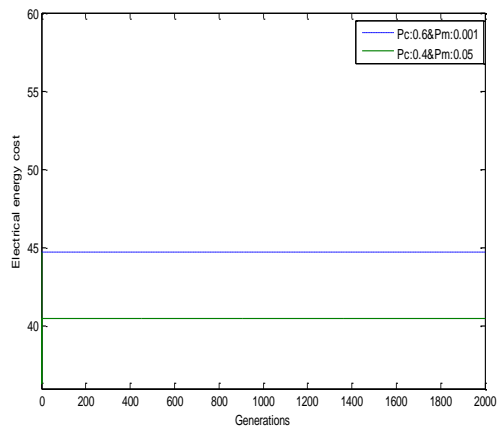


Figure 7 The electrical energy cost for C=200

After successive 100 trials, suitable parameters were obtained and are as presented in Table 2.

Table 2 System model parameters

Parameters Description	Parameters
Maximum Height in Reservoir h_{max}	4M
Minimum Height in Reservoir h_{min}	2m
Initial height in reservoir, h_{int}	3m
Off peak period tariff, C_L	0.2496RM
Peak Period C_H	0.3120RM
Number of chromosomes	200
Number of generation	2000
Mutation Probability	0.05
Selection Technique	Roulette Wheel
Crossover Probability	0.4
Elitism	Best 2 chromosomes

Figure 7 shows several selected performance test of fitness function versus generation. From these performance tests, the cost of electric energy are calculated and presented in Table 3. The results show the Test 1 produces the least electric energy cost with percentage difference index is about 34.97%. Test 2 to Test

5 give the same result with PDI is at 32.47%. These results show the consistencies of the AWGA in obtaining optimum result as within 3%. The goal of the optimization is to obtain an optimal pump schedule with reduced cost as given by Test 1.

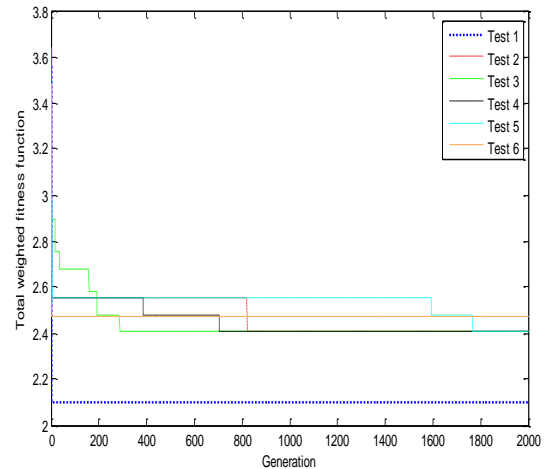


Figure 8 Total weighted fitness function versus generation

Table 3 Results of tests

Test	Electric Energy Cost (RM) (Current)	Electric Energy Cost (RM) (Proposed Optimization)	Percentage Difference Index (PDI) %
1	55.84	36.31	34.97
2	55.84	37.71	32.47
3	55.84	37.71	32.47
4	55.84	37.71	32.47
5	55.84	37.71	32.47
6	55.84	39.1	29.98

The level variation in the reservoir for Test 1 is presented in Figure 9. The changes in water level in the reservoir remain between 3m and 4m and meet water demand requirement.

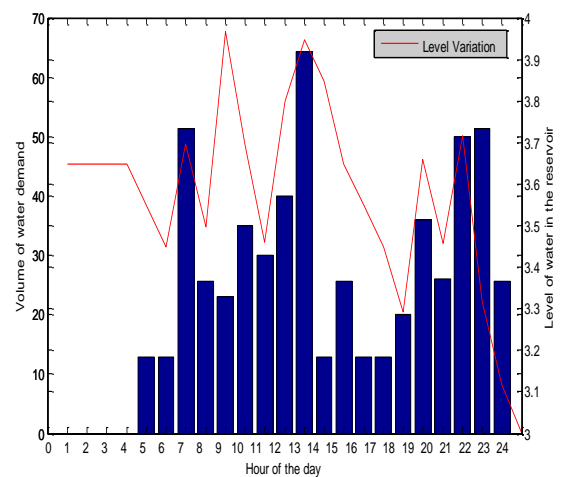


Figure 9 The level variation in reservoir versus demand profile

4.0 CONCLUSIONS

The application of the Adaptive Weighted sum Genetic Algorithm (AWGA) in the optimization of the electrical energy

consumption as well as the level reliability of the MJII, Beranang's water supply system has been presented herein. The algorithm has been tested using actual data sets from the supply system and the result obtained shows a significant and appreciable reduction of about 34.7% as compared to normal operations of the system without the application of the AWGA. Furthermore, the AWGA algorithm as also demonstrated a significant performance in attaining a reliable water level in the reservoir to cater for recovery of the initial water level and also emergency situations. However, more work is ongoing as to further improve on the robustness of the AWGA for application on the water supply system to ensure system efficiency and reliability during critical time such as in the dry seasons and periods of general water shortage.

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