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Design Optimization of 3-Phase Rectifier Power Transformers by Genetic Algorithm and Simulated Annealing



Abstract—This paper presents the design optimization, by Genetic Algorithm (GA) and Simulated Annealing (SA), of a 3-phase rectifier power transformer supplying a dc load. A closed form expression for actual phase current waveform of the rectifier transformer is used and a comparison is made with the approximate waveform normally considered for fixing the transformer rating. Two non-linear programming techniques, GA and SA are applied for the estimation of transformer design parameters and the results are compared. The optimal results demonstrated by an example show the potential for implementation of GA as an efficient search technique for design optimization of transformers. A discussion on the limitations and variation of GA parameters while minimizing the single and multi-objective functions satisfying the performance constraints on the proposed optimal design concludes the paper.

Keywords – Semi-conductor rectifier power transformers, non-sinusoidal currents, nonlinear programming, genetic algorithm, and simulated annealing.

I. INTRODUCTION

A rectifier power transformer followed by a 3-phase diode bridge rectifier to supply dc loads at a low voltage draw significant non-sinusoidal currents from the utility grid and need important considerations to meet the standards imposed by IEEE and IEC. In addition to the normal core and I^2R losses, the harmonic currents in the windings contribute additional I^2R losses. The construction, electrical characteristics and various types of connections of rectifier power transformers are presented in manufacturer's pamphlets and publications [1-3]. The optimal design procedure of a transformer employed for dc loads is different from a conventional power transformer. Powell's [4, 5] classical sequential unconstrained minimization technique together with Zangwill's exterior penalty function method [6] has been applied for conventional and special purpose transformers [7]. GA is proposed as a search method for optimal design of pole-face of a dc motor [8], induction motor parameters [9], surface mounted permanent magnet motor [10]. GA coupled with direct search method for the design of a dc motor [11] and an improved GA for single and double objective optimum design problems of power transformers [12] are reported. Also GA is compared with conventional methods [13] for the equivalent circuit parameter estimation of a three-winding transformer.

An overview of SA, practical implementation and a comparative study is presented [14]. Discrete-state SA technique is applied for optimization of preliminary design

problems of an air-craft [15]. In this paper, a procedure for developing the rating of a rectifier transformer and its optimal design using GA for single and multi-objective function minimizations is proposed. The results are compared with those obtained by SA for minimization of single objective functions. In practice, the KVA rating of a transformer is decided by the rms or fundamental component of current drawn from the grid, as recommended by IEEE or IEC respectively as published in [16, 17]. The static converting equipment, the transformer connection and the source impedance normally influence the primary and secondary winding currents as well as the input line current. In a two winding rectifier transformer, the primary HV winding is nearest to the iron core, while the heavy current secondary is on the outside and subdivided into a number of parallel coils [18]. The importance of proper kVA rating, additional losses due to non-sinusoidal currents are reported in this paper while estimating the optimal design of the transformer. The main focus of the design analysis program is on winding design, core losses, winding losses and thermal model. The present paper addresses a single and multi objective function design optimization by GA and SA for a medium size 3-phase rectifier power transformer.

II. PHASE CURRENT AND TRANSFORMER RATING

The resultant secondary phase current waveform of a 3-phase star-delta connected power transformer followed by a 3-phase, diode bridge rectifier, neglecting and considering the source impedance respectively, is as shown in Figs. 1 and 2. A closed form expression of the secondary phase rms current, I_2 for a dc load is derived with the assumptions:

- Direct current supplied to the load is without ripple.

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ii. Commutation overlap of the rectifying devices is neglected (Fig. 1) or commutation loop comprises only inductance (Fig. 2).

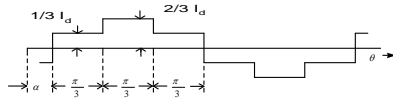


Fig. 1: Approximate phase current

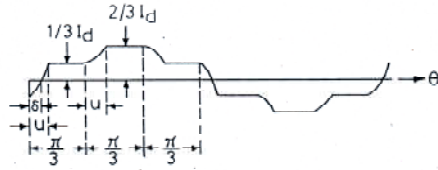


Fig. 2: Actual phase current

From Fig. 1, neglecting source inductance, the instantaneous current is

$$i(\theta) = \int_{\alpha}^{\alpha + \frac{\pi}{3}} \frac{I_d}{3} d\theta + \int_{\alpha + \frac{\pi}{3}}^{\alpha + \frac{2\pi}{3}} 2 \frac{I_d}{3} d\theta + \int_{\alpha + \frac{2\pi}{3}}^{\alpha + \pi} \frac{I_d}{3} d\theta \quad (1)$$

The total and fundamental component rms phase currents from (1), respectively, are derived as $I_{2rms} = \frac{\sqrt{2}}{3} I_d$,

$I_{2fms} = \frac{\sqrt{2}}{\pi} I_d$ Assuming a dc load current of 10000 A, the respective currents are, $I_{2rms} = 4714.05$ A, $I_{2fms} = 4500.32$ A and the ratio $I_{2rms} / I_{2fms} = 1.0475$.

Similarly from Fig. 2, assuming the current variation during the commutation intervals as cosine waves [7], the total instantaneous current is derived as,

$$i(\theta) = \int_0^{u-\delta} \left[\frac{2}{3} I_d \frac{1 - \cos(\theta - \delta)}{1 - \cos u} - \frac{1}{3} I_d \right] d\theta + \int_{u-\delta}^{\frac{\pi}{3}-\delta} \frac{1}{3} I_d d\theta + \int_{\frac{\pi}{3}-\delta+u}^{\frac{\pi}{3}-\delta+u} \left[\frac{1}{3} I_d + \frac{1}{3} I_d \frac{1 - \cos\{\theta - (\frac{\pi}{3} - \delta)\}}{1 - \cos u} \right] d\theta + \int_{\frac{\pi}{3}-\delta+u}^{\frac{2\pi}{3}-\delta} \left[\frac{2}{3} I_d \right] d\theta + \int_{\frac{2\pi}{3}-\delta+u}^{\frac{2\pi}{3}-\delta+u} \left[\frac{2}{3} I_d - \frac{1}{3} I_d \frac{1 - \cos\{\theta - (\frac{2\pi}{3} - \delta)\}}{1 - \cos u} \right] d\theta + \int_{\frac{2\pi}{3}-\delta+u}^{\pi-\delta} \left[\frac{1}{3} I_d \right] d\theta + \int_{\pi-\delta}^{\pi} \left[\frac{1}{3} I_d - \frac{2}{3} I_d \frac{1 - \cos\{\theta - (\pi - \delta)\}}{1 - \cos u} \right] d\theta \quad (2)$$

where u = overlap angle and

$$\delta = \cos^{-1} \left(\frac{1 + \cos u}{2} \right)$$

Assuming the same dc load current, Table 1 shows the computed values of current from (2) for different overlap angles. The assumption that the overlap angle varies from 5° up to 25° is based on the leakage reactance of the transformer and current at commutation.

TABLE I
COMPUTED VALUES FOR ACTUAL PHASE CURRENT

u	5°	10°	15°	20°	25°
$I_{2rms}(si)$	4686.1	4658.4	4630.6	4602.4	4573.9
$I_{2fms}(si)$	4610.8	4503.2	4489.5	4477.8	4463.9
$\frac{I_{2rms}(si)}{I_{2fms}(si)}$	1.016	1.0345	1.0314	1.0278	1.0246

As observed, the total rms current, $I_{2rms}(si)$ computed from Fig. 2, is more nearer to the actual current in the windings. Also it provides accurate estimation of eddy current losses in the windings, kVA rating, temperature rise etc. Following the IEEE standards the rms rated kVA is derived from Fig. 2 and for an initial design analysis in this paper, an overlap angle of 15° is assumed. The transformer kVA rating, S is then derived for a given dc load voltage, V_d and the transformer secondary phase current, I_2 as

$$S = 3 V_2 I_2 10^{-3} \quad (3)$$

where $V_2 = V_d \pi / (3\sqrt{2})$ = secondary winding rms phase voltage.

As an example for design optimization, in this paper, a 3-phase star/delta connected transformer supplying a dc load at 10,000 A, and 400 V is considered. As very high secondary currents over a wide secondary voltage range are to be regulated [3], 9 tap positions on high voltage winding, are considered. A medium primary voltage and a secondary voltage range to feed the stipulated power to the dc load are assumed. Thus the specifications of the transformer considered are 4 MVA, 33 kV / 270-330 V, star/delta, 3-phase core type with forced oil cooling.

III. OPTIMIZATION PROCEDURES WITH GA AND SA

A non-linear mathematical model is developed in this paper to investigate the optimal parameters of the rectifier transformer forming a fitness function. Optimal design problems require a search for the global minimum of the fitness function or objective function. As there is no single best method for non-linear optimization problems, a method based on characteristics of the problem to be solved is to be selected. Methods based on Artificial Neural Networks (ANN) evolve the fitness function to reach the nearest local minimum and stop there [19]. Training of the neural networks is an optimization problem itself. For global optimization, one way is to run any of the local optimization methods from numerous random starting points such as Powell's method [7]. Among many intelligent optimization techniques, GA and SA are two stochastic methods currently in wide use for difficult optimization problems [20].

While SA creates a new solution by modifying only one solution with a local move, GA creates solutions by combining two different solutions. Also GA is robust and far less sensitive to parameter values [21, 22], initial conditions as compared to SA. GA is based on natural selection, the process that drives biological evolution [23] and repeatedly modifies a population of initial solutions. It selects individuals at random from the current population, uses crossover and mutation operators, and over the successive generations, the population evolves toward an optimal

solution. In contrast to more traditional numerical techniques, the parallel nature of the stochastic search done by GA often makes it very effective to arrive at global optimum. Also GA offers a convenient way of handling constraints and a single or multi objective functions. In GA approach, each design variable represented as a binary string (chromosome) of fixed length is evaluated by using a fitness function. GA provides solutions by generating a set of chromosomes referred to as a generation. If the search has to continue, the GA creates a new generation from the old one until a decision is made on the convergence. A crossover operator exchanges information contained in two parent individuals to produce two offspring and then replace the parents. The number of times the crossover operator is applied to the population is determined by the probability of crossover and the population size. The mutation operator randomly selects an individual from the population and then chooses two elements in this individual to exchange positions. A binary tournament selection strategy is used to select the fittest individuals where two individuals are selected at random from the population, and the better one is duplicated in the next generation. This process is repeated until the individuals reach a specified population size.

The SA algorithm is based on the analogy between the annealing of solids and the problem of solving optimization problems. Annealing is the physical process of heating up a solid and then cooling it down slowly until it crystallizes. The states of the solid represent feasible solutions of the optimization problem, the energies of the states correspond to the values of the objective function computed at those solutions, the minimum energy state correspond to the optimal solution to the problem. The algorithm consists of a sequence of iterations and each iteration step randomly changes the current solution to create a new solution in the neighborhood of the current solution [14]. SA, a Monte Carlo method can be modeled mathematically using the theory of finite Markov chains. By definition, a Markov chain is a sequence of trials, where the probability of the outcome of a given trial depends only on the outcome of the previous trial. In the case of SA, a trial corresponds to a move, and the set of outcomes is given by a finite set of neighboring states. The convergence of the algorithm is governed by a set of parameters, known as a cooling schedule, are specified by an initial value of the control parameter (i.e. temperature), a decrement function for lowering the value of the control parameter, a final value of the control parameter specified by a stop criterion and a finite length of each homogeneous Markov chain. A candidate initial solution of design vector of variables is also required for initiating the process of minimization of an objective function.

IV. DESIGN ANALYSIS

A. Core and Windings

A three-legged core is adopted with HV continuous disc winding for the primary and LV helical winding for secondary. The LV winding consists of a number of multi-strand conductor coils connected in parallel and arranged one above the other.

B. Losses in the Transformer

The losses that affect the efficiency of the transformer are core, winding copper and stray load losses [24].

C. Core Losses

While the current waveform is distorted, the voltage impressed on the primary, when the rectifier is fed from a system whose capacity is reasonably large, approximates to a sine wave. A slight increase in the core losses due to the dc component of load current is neglected. The core losses in the core limbs and yoke are expressed as a sixth degree polynomial,

$$P_i = FF(B_c)G_i + 1.075 FF(B_y)G_y \quad (4)$$

Where $FF(\)$ is a polynomial to represent the core loss; B_c , B_y - flux densities; and G_c , G_y - weights.

D. I^2R and Eddy Current Losses

In addition to the normal I^2R losses, the HV and LV conductor eddy current losses are assumed to vary with the square of the rms current and square of the frequency. There are two approaches to evaluate eddy current losses with non-sinusoidal current:

- To derive a formula similar to eddy loss ratio with sinusoidal current.
- To determine the losses as sum of several contributions of harmonic components of actual current.

As the first approach is simple and convenient as the expression for rms current as derived [7] is available, the eddy loss ratio for an arbitrary wave shape of current is derived as [7, 18],

$$K_{e,pul} = \left(\frac{5m^2 - 1}{45} \frac{h_c^2 b_0^4}{h_w^2} \right) \left(\frac{I}{I'} \right)^2 \left(\frac{\mu_0}{\rho^2} \right) \quad (5)$$

where m - parallel conductors in radial direction; h_c , h_w - height of copper in axial direction and winding; b_0 - radial dimension of conductor; I , I' - RMS current and time derivative of RMS current per phase; μ_0 - magnetic space constant and ρ - specific resistance of copper.

E. Stray Losses and Temperature Rise

The stray losses in the core, core clamps, magnetic shields, enclosure or tank walls and other parts increase the temperature rise [24]. The winding and top oil temperature rises are computed [24] assuming forced liquid cooling considering total load losses for fundamental and harmonic currents.

V. OPTIMIZATION METHODS

The main focus in this paper is to derive optimal design parameters minimizing a single objective function such as volume, weight or cost of the transformer and a multi-objective function of the above. The active materials cost of stampings and windings copper are assumed in the ratio of 1:2 units. The cost function including the capitalized cost of transformer losses is expressed as [7]:

$$F_c(X) = c_i G_i + c_c G_c + c_1 P_c + c_2 P_i \quad (6)$$

where $X = (x_1, x_2, \dots, x_n)$, vector of design variables; c_i , c_c - cost of stampings and copper; c_1 , c_2 - loss capitalization factors; and G_c , G_i - weight of the copper and stampings.

Similarly the weight and volume functions are defined as:

$$F_w(X) = G_i + G_c \tag{7}$$

$$F_v(X) = V_i + V_c \tag{8}$$

where V_c, V_i - volume of copper and stampings.

In addition to the constraints the design variables are constrained with upper and lower bounds to satisfy mechanical and performance restrictions. The transformer mathematical model posed as a nonlinear programming problem [4] is stated as:

Find X such that $F(X)$ is a minimum, subject to $g_j(X) \leq 0, j = 1, 2, \dots, m$ with $X \geq 0$ being a non-negative solution. $F(X)$ and $g_j(X)$ are the nonlinear objective and constraint functions. Using exterior penalty function method [6] an augmented objective function, P is formulated as:

$$P(X, r) = F(X) + r \sum_{j=1}^m [g_j(X)]^2, r \geq 0 \tag{9}$$

where r is the penalty factor.

The next step is to select appropriate design variables and constraints for the optimization problem. In both GA and SA methods, six design variables and six constraints are selected on the basis of core geometry, losses in core and windings, short-circuit impedance, temperature rise, weight, volume and finally on the cost of the transformer. The objective and constraint functions are developed in terms of the specified design variables - x_1 Maximum flux density in the core, x_2 Current density in hv winding, x_3 Current density in lv winding, x_4 Height of the windings, x_5 Voltage per turn, and x_6 Distance between core centers. The general optimization program includes the main design analysis program together with seven function programs, viz., HV continuous disc winding with tap settings, LV helical winding, temperature rise of windings and oil, mechanical forces in windings, GA or SA optimization program etc. In GA method each design variable is coded as a 16 bit binary string. The design optimization simulations are experimented with GA and SA for single objective functions, and then multi-objective function minimizations with GA as a tool.

VI. RESULTS AND DISCUSSION

The design optimization minimizing the objective functions are derived by both GA and SA methods. Two different approaches are proposed and implemented with GA simulations. The first method of solution uses the augmented objective function with a penalty factor and constraints. In the second method the constraints are also treated as variables for minimization of the normal objective function. The GA technique is initially experimented with population sizes of 25, 50, 75 and 100, and for different mutation and crossover probabilities. After experimenting for different combinations, better global optimal results are returned with a population size of 100, probability of mutation as 0.044 and probability of cross-over as 0.866. It is observed that GA cause premature convergence if the penalty factor

selected is too large. The algorithm was run with penalty factors of 5, 3 and 0.001 respectively for cost, weight and volume objective functions, and for a variation of number of generations from 100 to 600.

The accuracy of the SA optimization depends on the cooling rate and the number of iterations. Determining the SA parameters is a challenge with annealing. After experimenting SA simulations with different combinations, better optimal results are returned with the initial temperature as 125 °C, the factor for reducing the initial temperature as 0.98, the factor for reducing the neighborhood size as 0.75, the Markov chain length as 200, and maximum number of iterations as 600. The optimal minimum cost without constraint violations is returned, as the number of iterations is increased from 100 to 600. The optimal single objective functions are presented in Figs. 3 to 5. For GA method, index 1 in Figs. 3 to 5 indicates the minimizations of augmented objective functions. Index 2 represents the minimization of normal objective functions when constraints are treated as variables like design variables.

It is observed from Fig. 3 that global minimum for cost is reached around 200 generations in GA and after 500 iterations in SA. The minimum cost obtained by GA is much lower than by SA. As the active materials cost of stampings and winding copper is in the ratio of 1:2 units, the cost function is represented in units. The results on minimum weight for the same GA and SA parameters are presented in Fig. 4, show that the optimum weight obtained by GA after 200 generations is little higher than by SA after 600 iterations. Simulation experiments for the volume of active materials returned the results as shown in Fig. 5 and the optimum value is reached after 100 generations in GA and after 600 iterations with SA.

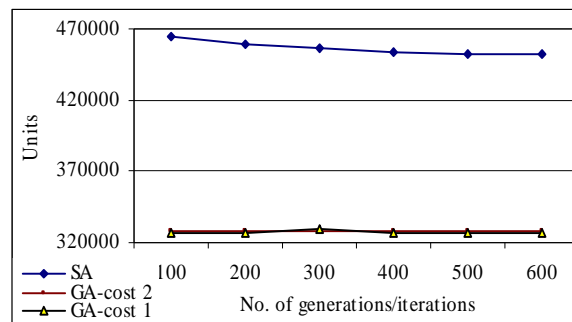


Fig. 3: Cost objective function

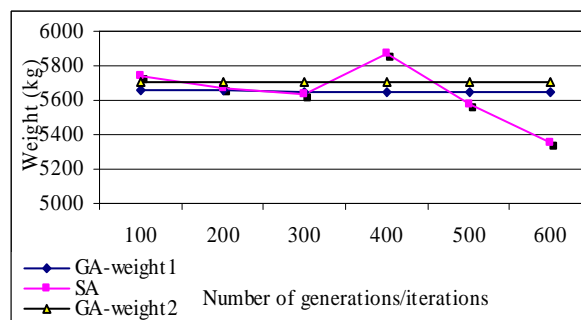


Fig. 4: Weight objective function

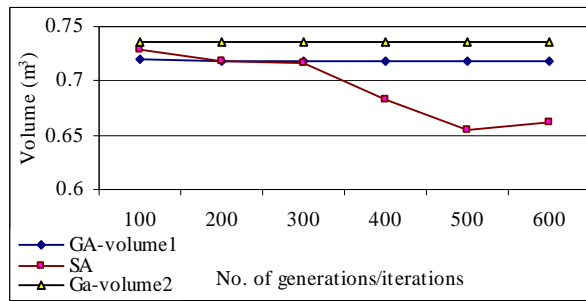


Fig. 5: Volume objective function

In GA technique the design variables are randomly generated and the global optimal solutions are obtained after a predefined number of generations. An initial solution of design vector of variables is required in SA for initiating the process of optimization. In both the methods the augmented objective functions are minimized but with different penalty factors.

A realistic comparison for the optimal design variables and constraints for minimum cost obtained by GA/SA techniques after 600 generations/iterations are reported in TABLE II. It is observed from the simulations that global optimal solutions resulted in less computational time with GA method. Thus GA technique has proved to be an effective tool for transformer design optimization.

TABLE II
DESIGN VARIABLES AND CONSTRAINTS

Design variables	SA	GA
x_1 Maximum flux density in the core, T	1.68	1.68
x_2 Current density in hv winding, A/mm ²	2.44	2.25
x_3 Current density in lv winding, A/mm ²	2.60	2.50
x_4 Height of the windings, m	0.61	0.90
x_5 Voltage per turn, V	28.0	34.86
x_6 Distance between core centers, m	0.56	0.60
Constraints		
1. Temperature rise of windings above ambient, °C	51.00	54.83
2. Temperature rise of oil above ambient, °C	42.00	44.84
3. % Short circuit impedance	2.50	3.29
4. % No-load current	2.50	2.79
5. % Efficiency	98.00	99.18
6. Clearance between different phase windings, m	0.04	0.03

As the results obtained for single objective functions using GA is found to be encouraging, minimization of multi-objective functions with different weight coefficients and penalty factors for the transformer problem is proposed in this paper. Three different multi-objective functions are formed from the normal and augmented objective functions. Using the weight coefficients for normal objective functions, multi-obj-1 is formed. The sum of augmented objective functions is multi-obj-2 and multi-obj-3 is the sum of augmented objective functions formed from normal objective functions with weight coefficients. A combined multi-objective function from the single objective functions, using (6) to (8), returned global optimal solutions similar to single-objective functions. Fig. 6 shows, the trend of minimization of three different forms of multi-objective functions using weight coefficients and penalty factors, as

functions of the generation number. The weight coefficients for cost, weight, and volume respectively are 0.5, 23.5 and 19e+03, selected from several combinations, after a number of experimental simulations.

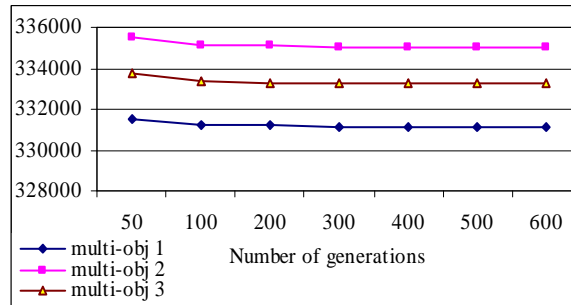


Fig. 6: Multi-objective function

TABLE III
OPTIMAL VALUES OF RECTIFIER TRANSFORMER

<u>HV continuous disc winding</u>	
Turns per phase	566
Number of coils	80
Width of the winding, mm	37.83
Normal conductor dimensions, mm	3.28 x 1.25
<u>LV helical winding</u>	
Turns per phase	8
Number of coils	18
Number of parallel conductors	6
Width of the winding, mm	28.19
Conductor dimensions, mm	4.94 x 3.45
<u>Other design parameters</u>	
Core circle diameter, m	0.39
Width of the core, m	1.55
Height of the core, m	1.12
Dimensions of the tank, m	1.42 x 2.61 x 2.28
Secondary voltages, V	270, 276, 283, 290, 297, 305, 312, 321, 330
Overlap angle of the rectifier, deg.	22.01

The results as shown in Fig. 6 are satisfactory and the global optimum value is reached after 200 generations. As observed the deviations of function values in Figs. 3 to 5 for index 1 and 2 and also in Fig. 6, is only a small percentage, confirms the global minimum. The design analysis program returns optimal design values at the end of every simulation for a specified number of generations in GA and for specified iterations in SA. The optimal design parameters returned by both the methods are very close. For 600 generations, the optimal parameters and main design values of the transformer, minimizing the cost with the first method using GA are presented in TABLE III.

The results of the complete design analysis program reported in Tables 2 and 3 are satisfactory and GA optimization process returned similar values while minimizing weight or volume or a multi-objective function. It is observed that GA algorithm is superior over SA to handle the constraints and in each minimization of objective functions, the GA outperformed SA.

VII. CONCLUSIONS

A new procedure for design optimization of 3-phase semi-conductor rectifier power transformers using GA/SA for single and with GA for multi-objective function minimizations is proposed in this paper. A closed form expression for actual phase current waveform of the rectifier transformer is used and the KVA rating is developed conforming IEEE standards. The GA technique has proved to be superior over the SA method for obtaining global optimal solutions. The transformer design optimization for single or multi-objective function minimizations resulted in satisfactory optimal design parameters and design data as demonstrated by an example.

VIII. ACKNOWLEDGMENT

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X. BIOGRAPHIES



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