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A new genetic algorithm to optimize synchronous machine controls in statically reduced power system models ⋆

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ABSTRACT

The development of new power grid components and solutions requires dynamic grid simulations, including vast transmission grids. These simulations are often prohibitively computationally expensive. Static model reduction is a common solution to reduce the complexity of grid models. However, these reduction techniques do not consider the control structure of synchronous machines. As a result, the models lose the ability to be simulated dynamically. To address this issue, we introduce a new genetic algorithm that optimizes these controls in previously reduced models. This enables dynamic simulations for models previously reduced with arbitrary static reduction methods. The new method optimizes the selection and parameters of synchronous machine controls to approximate the original system behavior. We evaluate the new method using a standard IEEE benchmark model and demonstrate its applicability with a real-world transmission grid model with more than 300 nodes.

1. Introduction

Solving the challenges the transmission grid faces in the course of the energy transition requires the static and dynamic simulation of these vast systems to identify issues and to develop respective solutions. The sheer size and complexity of transmission grids, however, is often a limiting factor, especially for dynamic real-time simulations, which are crucial for hardware-in-the-loop (HiL) testing with real-time simulators, such as RTDS [1], when developing new grid components.

Traditional network reduction techniques, such as the (extended) Ward reduction [2,3] or the radial, equivalent, and independent (REI) method [4], are commonly used in the industry for the generation of static network equivalents. For dynamic simulations, [5] introduces methods to aggregate generators and the corresponding controls based on aggregated transfer functions of coherent generator groups. In [6], a method used for active distribution networks is presented, utilizing artificial neural networks (ANNs) and identification for dynamic equivalents. After clustering the system states, an ANN is trained on recorded or simulated events for every cluster to estimate robust parameters for a variable-order dynamic equivalent model. A dynamic reduction method is proposed in [7], which yields a purely synthetic equivalent by placing a given number of generators in a reduced network and performing a parameter optimization to match the equivalent system behavior to the original. Kuri et al. [8,9] combine the common REI reduction [4] with a coherency-based generator aggregation and subsequent parameter tuning with a genetic algorithm (GA). They aim to minimize the difference between the response curves of selected variables of the original and the reduced model. This is achieved by using the improved non-dominated sorting genetic algorithm (NSGA-II) that is specialized on multi-objective optimization [10]. Similarly, [11] uses a GA for dynamic load modeling, essentially replacing a distribution grid model with a simplified equivalent with a fixed structure. For electromagnetic transient (EMT) simulations, the frequency-dependent network equivalent (FDNE) is a common approach to create wideband multi-port equivalent models, implemented, e.g., in PSCAD and RSCAD [12]. The FDNE is a multi-port admittance matrix whose elements are rational polynomials that can be determined by fitting the frequency response of the FDNE to the original model [13]. These FDNE blocks are used to represent the high-frequency characteristics of the system and can be combined with phasor-based models for the slower electromechanical behavior [13].

Depending on the use case, there are different desirable properties for equivalent models: Having a physical model—where the equivalent model consists of equations that represent physical units [14]—increases the interpretability of the equivalent compared to non-physical models. For studies of systems with large shares of renewable energy generation, geographic information becomes a deciding factor [15]. To the best of our knowledge, there are no network reduction methods for dynamic simulations that provide both of these

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properties at the same time. There are, however, reduction methods for *static* simulations that do so, such as topology-preserving network reduction (TPNR) [16]. Therefore, the goal of the present work is to develop a method that enables dynamic simulations for transmission grid models statically reduced with existing reduction methods, including such methods that preserve geographic information. This new method is based on the observation that the dynamic behavior of a transmission grid model is highly influenced by the generator controllers, e.g., exciters, governors, and power system stabilizers (PSSs). Therefore, the fundamental idea in the present work is to find a suitable controller configuration for the generators in the reduced model to approximate the dynamic behavior of the detailed model. We propose a new method based on a GA to select suitable controller models and their parameters. In addition to the *physical model* criterion identified above, this method aims to approximate the dynamic behavior by only using standard controller models for maximum compatibility with common modeling software.

The remainder of this work is structured as follows: In Section 2, we introduce our new methodology in detail. Section 3 follows with its evaluation, using a benchmark system and a real-world example. In Section 4, we discuss the results of the evaluation before concluding this work in Section 5.

2. Method: Genetic algorithm-based controller optimization

This section formally describes the problem of approximating the dynamic system behavior, as well as our new methodology of using a GA to optimize the generator controls of a statically reduced power system model to achieve this approximation. We denote the original, detailed power system model as M and the reduced model as $\hat{M}$. To describe the dynamic behavior of the two systems, we define a set of events $\mathcal{E}$ and variables $\mathcal{V}$ in both models. The combination of an event $e \in \mathcal{E}$ and a variable $v \in \mathcal{V}$ defines an objective $o = (e, v) \in \mathcal{O}$. Typical events might include short circuits, load changes, and switch openings or closings, representing various planned and unplanned changes in the grid. Variables of interest could include voltages at the boundary buses or significant buses throughout the grid, power generation of important generators, frequencies in different areas of the grid, and power flows over crucial transmission lines. The defined events $\mathcal{E}$ are simulated, and the resulting values of the variables $\mathcal{V}$ are recorded as time series. The results for all objectives are stored in matrices X and $\hat{X}$ for the two models, respectively. With T time steps in each simulation, this leads to a size of $|\mathcal{O}| \times T$ for X, where $X[o, t]$ contains the t-th value of objective o. The goal of the optimization is, thus, to find a suitable controller configuration in the reduced model $\hat{M}$ that minimizes the difference between X and $\hat{X}$.

Eiben and Smith [17] make a clear “distinction between (search) problems
—which define search spaces—and problem solvers—which are methods that tell us how to move through search spaces.” For the problem at hand, the search space is the set of all possible generator control configurations, which includes the selection of controller models and their parameterization. Due to the complexity of power grid models, the relation between the adjustable parameters, and the model output $\hat{X}$ is prohibitively complex. Thus, optimizing the controller configuration of the reduced model $\hat{M}$ to approximate the output X of the detailed model M can be viewed as a search problem.

For the specific problem at hand, GAs are particularly suited for several reasons: they have proven effective for multi-objective optimization [10], are flexible enough to accommodate for the complex constraints on the model parameters, and are a widely used method to solve search problems [18]. The effectiveness of GAs for the optimization of model parameters to approximate the dynamic behavior of a detailed model with a reduced-complexity equivalent is demonstrated in previous works [8,9,11]. In the following, we introduce, in detail, how our proposed method builds on these existing works to overcome their limitations and achieve the desired properties identified in the introduction: The optimization process starts with setting up the detailed model M and the reduced model $\hat{M}$ for simulations to describe the dynamic behavior of the two models. Section 2.1 follows with the genetic representation of the solution space and the creation of an initial population using this representation. In Section 2.2, we introduce the fitness function that is used to determine the performance of the individual solutions. Based on these fitness values, Section 2.3 describes the selection process for solutions to pass on their genes, i.e., parameters, and the procedure to compile the next generation of solutions. Sections 2.4 and 2.5 describe the crossover and mutation operators, respectively, that are used to create offspring from the previously selected parent solutions. Finally, Section 2.6 describes the method to select a single best solution to parameterize the synchronous machine controllers of the reduced power system model.

2.1. Genetic representation of individual solutions

A central part of every genetic algorithm is the representation of the solutions as chromosomes. This section describes the general structure of this representation and the methods to create valid chromosomes and an initial population for the optimization procedure. To optimize the controllers, i.e., exciter, governor, and PSS, of the aggregated generators, the chromosome needs to include (1) the specific controller model used to control the corresponding generator and (2) the parameters of this controller model. The proposed genetic representation comprises an ordered list of all aggregated generators and a chromosome, as illustrated in Fig. 1. This chromosome describes the controller model using a selector parameter and the model parameters for the specific model for every aggregated generator in the reduced power system model $\hat{M}$. The genetic representation is implemented for IEEE ST1A, AC1A, and simplified excitation system (SEXS) exciters [19], IEEE G1, TGOV1, HYGOV, and GAST governors [20], and IEEE PSS1A, PSS2A, and no PSS [21]. These models are a selection of controller models commonly found in the literature and available in common modeling software. Not all controller models require the same number of parameters. Thus, padding with zero values is used to ensure a consistent chromosome length for all variations. In total, the chromosome consists of 62 genes per generator.

2.1.1. Generating valid controller configurations

To gain valid configurations of controllers, the values that can be applied to the model parameters need to meet certain requirements. The controllers utilized for this optimization exhibit three types of parameter restrictions: (1) upper and lower bounds, (2) constraints depending on other parameters, and (3) integer constraints. Upper and lower bounds apply to all model parameters. When generating a new individual, parameters with only this constraint are simply set to a random value selected uniformly from the valid range. Constraints depending on other parameters often describe the requirement that one parameter value is greater than another. This can be implemented by selecting the first parameter and using the resulting value as a limit for the second parameter. However, other dependencies between parameters are possible, which might require different selection methods. The last type of constraint are integer constraints. These constraints typically describe structural options of the controllers, such as the selection of inputs. There are, however, more complex cases for integer constraints.

2.1.2. Generating the initial population

The proposed optimization method has two options for generating an initial population P, depending on the available system information. By default, without information on the original controls, randomly generated control configurations are assigned to the generators in the reduced system. For each of these generators, one valid controller configuration per type is generated at random and combined with the model selectors and padding to fit the required chromosome structure. As a second option, it might be beneficial to consider the original controllers for the

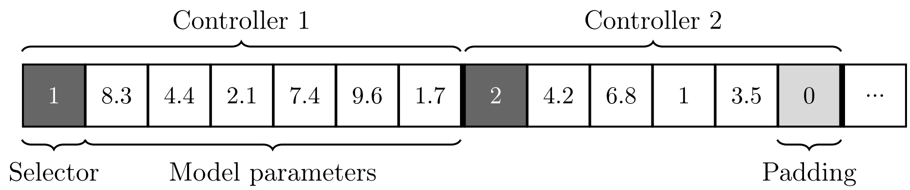


Fig. 1. An illustration of the genetic representation used to define a solution. For every aggregated generator, it describes the model and parameter values for its exciter, governor, and PSS. Padding with zero values is used to ensure a consistent chromosome length.

initialization of the population P if this information is available, e.g., when reducing a model with the TPNR method [16]. While using the same controllers as the detailed model does not necessarily lead to a similar behavior of the reduced model, it can be a good starting point for the optimization process. To generate the initial population P, the ratings of the aggregated generators are used to perform a weighted random selection of the original controller configurations. This approach can be used to completely or partly generate the initial population P in combination with the purely random approach described above.

2.2. Fitness function

A crucial part of the optimization is the fitness function F, which describes the performance of an individual solution $p \in P$. The proposed method performs a multi-objective optimization, meaning that it considers multiple objectives $o \in \mathcal{O}$ to determine the overall fitness of a solution. As defined above, these objectives are a combination of the simulated event e and the recorded system variable v, thus $\mathcal{O} \subset \mathcal{E} \times \mathcal{V}$. The matrix X contains the values resulting from simulating all events $\mathcal{E}$ with the detailed model M, and $\hat{X}_p$ describes the corresponding results from the reduced model $\hat{M}$ using the parameters of p. To describe the difference between the target and the achieved values, we use the mean absolute error (MAE), which describes the average of the absolute errors between two sets of values and is defined as

$$\mathrm{MAE}_o(\hat{X}_p) = \frac{1}{T} \sum_{t=1}^{T} \left| X[o,t] - \hat{X}_p[o,t] \right|, \tag{1}$$

where T is the number of time steps and $X[o,t]$ is the t-th value of objective variable o. We choose the MAE as it is stable around zero, does not have a bias for over- or under-estimation, and is easy to interpret. As the different objectives are evaluated individually, different scales for these errors do not influence the optimization process. Although different time frames after a simulated event have varying importance, we choose equally weight the whole simulation time. Our rationale is to avoid an application-specific bias and overfitting for a short time frame while producing significant deviations for less crucial time frames. The goal of the genetic algorithm is to find solutions with a high fitness. Since the defined error value increases with poorer results, it cannot be used directly as a fitness function. Instead, the fitness function for objective o of individual p is defined as

$$F_o(p) = \begin{cases} -1 \cdot \mathrm{MAE}_o(\hat{X}_p) & \text{if simulation completes,} \\ -10^{15} & \text{else.} \end{cases} \tag{2}$$

The value -10^{15} is chosen as an arbitrarily small number that should be several orders of magnitude smaller than the worst completing simulations. Mapping all failing individuals to the same vector with such a low fitness aims to ensure a fast exclusion of these individuals from further generations. The overall fitness, $F(p)$, is a vector consisting of the fitness values of all objective variables $F_o(p)$.

2.3. Parent selection and compilation of the next population

The first genetic operator is the selection of individuals for the mating process. The proposed method adopts parts of the NSGA-II algorithm, as this algorithm is designed for fast multi-objective optimization [10], which is well-suited for the potentially large number of objectives when optimizing, e.g., the voltages and frequencies of the boundary buses in a reduced model. A key mechanism in NSGA-II is elitism, meaning that the individuals with the highest fitness are guaranteed to move forward to the next generation. The proposed method applies elitism with 50 % of the population, and the other half is formed by selection, crossover, and mutation.

To determine the individuals for mating, NSGA-II introduced the crowded-comparison in [10]. Selecting individuals based on this crowded-comparison operator prefers individuals with a lower rank and individuals with more distance to comparable individuals regarding their fitness to yield a well-performing set of solutions with high diversity. One half of the next generation is created by sorting all solutions using this crowded-comparison operator and selecting the first $\mathrm{N_P}/2$ individuals. The other half is created through crossover and mutation. Since every crossover operation combines two parent individuals to form one offspring individual, $\mathrm{N_P}$ individuals are selected from the current population P for mating, with a tournament selection method: two individuals are selected randomly and compared with the crowded-comparison operator, and the individual with the lower value is chosen for the mating pool. The tournament-based selection allows individuals from all ranks to get selected for mating, resulting in a larger diversity without risking the loss of well-performing individuals because of elitism.

2.4. Crossover

The crossover is the second genetic operator, expanding the search space and creating the next generation from individuals of the current one, usually by combining two parent individuals to one offspring individual. As such, there exists a wide variety of crossover operators for general optimization problems [22]. However, it is often beneficial to adapt the crossover operator to the problem at hand. As the controller parameters have very specific requirements, we propose a crossover operator specifically for this problem. This crossover operator is performed piecewise for every controller encoded in the chromosome with a certain probability $\mathrm{p_c}$. If a random variable is not greater than $\mathrm{p_c}$, the controller models of both parents are compared and, if they have the same model type, are combined via arithmetic crossover, defined as

$$C_i = A_i + r_i(B_i - A_i), \quad 0 \le r_i \le 1, \tag{3}$$

where A_i and B_i are the i-th controller of the parents and C_i is the resulting offspring controller. The variable r_i is randomly selected for each application of the operator and determines where the offspring lies between both parents. If the controller types do not match, one parent controller is selected randomly as offspring controller. The arithmetic crossover in Eq. (3) produces valid parameter values regarding parameter limits and linear parameter constraints, but does not necessarily yield valid configurations regarding integer constraints or more complex conditional constraints. Thus, it might be necessary for some controller models to check and potentially correct the created configurations, e.g., by rounding parameters to integers.

2.5. Mutation

Mutation is the third type of genetic operator central to all genetic algorithms, which randomly alters one individual to create one offspring individual [17]. We propose a mutation operator specifically for the problem at hand. Analogous to the crossover operator, the mutation is performed by iterating over the controllers defined in the parent. With a probability of p_m, a controller is mutated using one of two methods: In the first case, with a probability of p_{tm}, an entirely new controller instance is created and used for the offspring. In the other case, a new controller instance B_i is created, and a scaled arithmetic crossover is calculated between B_i and the single parent A_i, as follows

$$C_i = A_i + r_i \cdot s_m(B_i - A_i), \quad 0 \le r_i \le 1, \quad 0 \le s_m \le 1, \tag{4}$$

where r_i is selected randomly for every application of the operator and s_m is a global parameter that defines the strength of the mutation. Lower values of s_m generally lead to the offspring being closer to the parent, while higher values result in stronger mutations.

2.6. Selecting the best individual

The final step of the parameter optimization is the selection of the set of parameters with the best results. However, the potentially high dimensionality of the fitness vectors, $F(p)$, likely results in non-dominating solutions, where no single solution has the highest fitness for all objectives. Thus, we define $f(p)$ to describe the fitness of an individual p with a one-dimensional value as follows:

$$f(p) = \sum_{o \in \mathcal{O}} \left(F_o(p) / \min_{p \in P_c} F_o(p) \right), \tag{5}$$

where P_c is the population of individuals that complete the simulations successfully. Dividing the fitness values of each objective by the minimum fitness achieved for this objective effectively normalizes the values to the interval $[0, 1]$, resulting in a better comparability of the different objectives. With this normalized fitness, originally small fitness values $F_o(p)$, result in larger normalized values. Thus, the individual with the minimal summarized fitness $f(p)$ is selected as the best solution. Depending on the use case for the reduced model, a weighted summation of the individual objectives might be beneficial. The proposed single fitness value f, however, assigns the same weight to all objectives.

3. Evaluation

In this section, we evaluate an implementation of the proposed GA-based method to optimize controller parameters in reduced power systems $\hat{M}$ to approximate their detailed counterparts M. The method is implemented in Python for DIgSILENT PowerFactory [23] models and utilizes the PyGAD package [24] as a framework for the GA. For the evaluation, two models are utilized: The IEEE 39 Bus System is used as a benchmark model as it is widely known and used in the literature. A much larger and more detailed transmission grid model of the German state of Baden-WÃ¼rttemberg (BW) is used to provide insights on a more realistic use case. These two models are described and evaluated in Section 3.1 and Section 3.2, respectively.

To evaluate the proposed method, the six parameters defining the process need to be set. For this purpose, a systematic evaluation of these parameters is performed by optimizing the IEEE 39 Bus System. With an initial testing, a population size N_P of 50 and 50 generations N_G are found to strike a good balance between runtime, diversity per generation, and improvement of generations over time. Out of 36 parameter sets for p_c, p_m, p_{tm}, and s_m, $(0.2, 0.5, 0.2, 0.1)$ is found to produce the best results on average, regarding the one-dimensional fitness f (see Eq. (5)), with a small variance between the different optimization runs. Therefore, these parameter values are selected for the evaluation.

To analyze the optimization results quantitatively by calculating the difference of the response of the reduced model $\hat{M}$ to the detailed model M, we use the MAE as defined in Eq. (1) and the mean absolute percentage error (MAPE), which is similarly defined as

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\hat{x}_i - x_i}{x_i} \right| \cdot 100\%. \tag{6}$$

The MAPE provides comparable error measures for the different variables that vary significantly in their typical range of values, while the MAE provides additional context in cases with values close to zero, which decrease the significance of the MAPE. In the following, the variables that are evaluated by an error measure are indicated with a subscript to the error measure, e.g., $\text{MAPE}_{B,u}$ is calculated for the voltage u of the boundary buses B.

To interpret the results, we define quality criteria for the different variables. Frequency variables have the smallest margin for error due to the narrow European grid limits. In Germany, manual countermeasures are triggered at 0.2 Hz deviations (0.4 % of 50 Hz) [25]. Model reduction errors should be an order of magnitude smaller than this. Voltage criteria are more relaxed, with allowed bands of 7 % to 10 % for the extra high and high voltage level [25]. Approximation errors should be below 0.5 %. For the active and reactive power of the generators, the criteria are less clear. For many applications, a low single-digit percentage error should be fine, but cases with stricter requirements might exist. To assess the system stability, the reduced model $\hat{M}$ should be unstable under the same conditions as the original M.

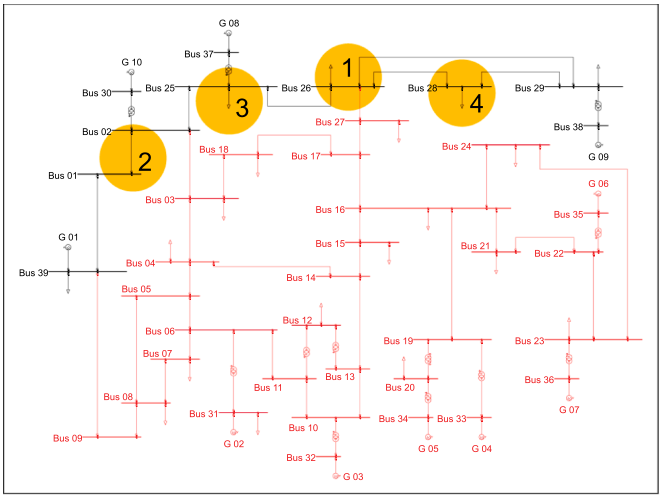
3.1. IEEE 39 bus system

The IEEE 39 Bus System is a commonly used model of a high-voltage transmission grid and serves as a benchmark model for the method proposed in the present work, as it is also used in comparable methods [8,9]. For this evaluation, the model is adapted from DIgSILENT PowerFactory 2022, as shown in Fig. 2a. The ten synchronous machines in the system are equipped with a mix of IEEE G1 and GAST governors, IEEE ST1A and AC1A exciters, and IEEE PSS1A and PSS2A, as well as deactivated PSSs. A reduced version of this model is obtained by applying PowerFactory's REI reduction method to the red area, resulting in the model shown in Fig. 2b. The number of buses is reduced by 24 and the number of generators by 4.

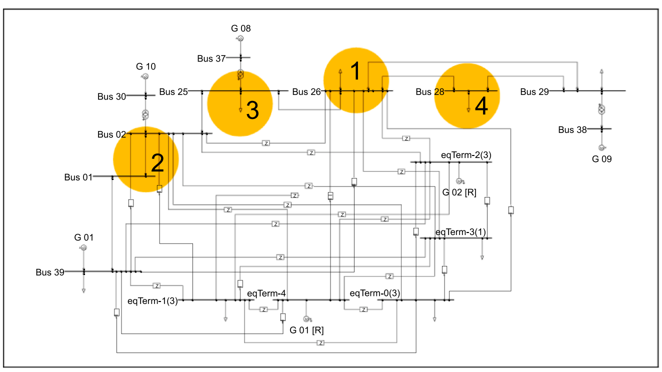
To assess the system behavior, we define the following four simulation events with their respective locations highlighted as yellow circles in Fig. 2: (1) A three-phase short-circuit at *Bus 26* after 5 s with 0 Ω impedance, that is cleared after 0.1 s. This event is also used in [8] and aims to provide a basic comparability between the two approaches. (2) Opening the switch at *Bus 01*, that connects it to *Bus 02* via a transmission line after 0.2 s. (3) A step load increase at *Bus 25* by 50 % after 0.2 s. (4) Ramping up the load at *Bus 28* by 50 %, between 1 s and 6 s.

To the best of our knowledge, the comparison between different equivalencing methods is very uncommon in the literature, probably due to the lack of information on the used models and missing details regarding the methods, significantly complicating a reimplementation of those methods. A comparison with industry standard methods, such as pure REI, would not be meaningful, since these methods do not consider the controls of aggregated generators. Nevertheless, we establish a base level of comparability with other methods by two means: (1) To get a sense of the quality of the results, we use the IEEE 39 Bus System with the same external system and short-circuit event as in [8]. (2) We utilize knowledge of the original and the reduced model to determine a likely suitable controller configuration manually. As the reduced generator *G 01 [R]* is equal to the original generator *G 02*, we choose the same controllers for the reduced generator. The controllers for *G 02 [R]* are based on the aggregated generators weighted by rating. This Manual Rating-based Configuration (MRBC) serves as a benchmark.

As objective variables, we select the voltage and frequency at the three boundary buses, as well as the active and reactive power and frequency of the retained synchronous machines. All optimizations were



(a) Original network



(b) Reduced network

Fig. 2. The original and reduced version of the IEEE 39 Bus System used for the evaluation with highlighted locations of simulated events. The reduced model is obtained by applying PowerFactory's REI reduction on the red area.

Table 1
The quantitative analysis of the reduced equivalent models: The models optimized by the GA on the short-circuit only (GA-SC) show a significant advantage over the other models, but the GA-optimized models using multiple events (GA-ME) show the overall best results. For the two load events, there is a slight advantage for the MRBC solution. Notably, the results for the three unseen events for the GA-SC models are still acceptable.

	Short-circuit			Switch		
	GA-ME	GA-SC	MRBC	GA-ME	GA-SC	MRBC
$MAPE_{B,u}$ [%]	0.3821	0.2790	0.6653	0.1556	0.1724	0.4048
$MAPE_{B,f}$ [%]	0.0140	0.0094	0.0229	0.0051	0.0060	0.0173
$MAPE_{G,P}$ [%]	1.3135	0.9760	2.3985	0.1846	0.2023	0.4941
$MAE_{G,P}$ [MW]	4.5085	3.1865	8.4794	0.7249	0.7954	1.9508
$MAPE_{G,Q}$ [%]	123.6288	81.6711	246.5924	86.6038	91.8131	344.5740
$MAE_{G,Q}$ [Mvar]	4.1959	3.1655	6.9371	2.2675	2.5051	5.5524
$MAPE_{G,f}$ [%]	0.0135	0.0089	0.0230	0.0051	0.0059	0.0161
	Load step			Load ramp		
	GA-ME	GA-SC	MRBC	GA-ME	GA-SC	MRBC
$MAPE_{B,u}$ [%]	0.0427	0.0551	0.0441	0.0405	0.0503	0.0413
$MAPE_{B,f}$ [%]	0.0077	0.0134	0.0038	0.0071	0.0123	0.0035
$MAPE_{G,P}$ [%]	0.1239	0.2232	0.1149	0.1204	0.2049	0.1436
$MAE_{G,P}$ [MW]	0.4983	0.9441	0.4535	0.4910	0.8649	0.5452
$MAPE_{G,Q}$ [%]	6.7764	9.9218	6.0104	17.0128	26.7607	13.9300
$MAE_{G,Q}$ [Mvar]	0.7574	1.1588	0.6751	0.6887	1.0393	0.6587
$MAPE_{G,f}$ [%]	0.0078	0.0134	0.0038	0.0071	0.0123	0.0034

Table 2
An overview of the system components of the BW model within the AoI, the external system, and the reduced equivalent of this external area.

	AoI	External	Reduced	Reduction [%]
Buses	128	177	104	41.2
Synch. machines	30	42	22	47.6
Static generators	166	268	83	69.0
Loads	96	131	45	65.6
Transformers	50	90	69	23.3
Transmission lines	68	85	46	45.9

performed for 50 generations with a population size of 50 aiming to optimize all four events simultaneously (GA-ME) and only the short-circuit (GA-SC). More generations and larger populations have shown diminishing effects in our testing. To reduce the effect of randomness in the optimization process, all optimizations were repeated ten times, using the mean values of these independent runs for the comparison. Exemplary results of the short-circuit simulation are shown in Fig. 3, comparing the reduced model with GA-optimized and MRBC parameters to the detailed model. These visual results are confirmed with the quantitative analysis in Table 1. The GA-optimized models clearly outperform the MRBC solution for the first two events with on average 56 % and 32 % the MAE values. For the two load events, the MRBC solution performs slightly better overall with 77 % and 80 % the error values of the GA, respectively. The inclusion of the GA-SC variant demonstrates that the optimization for a single event can yield more accurate results for this event, sacrificing some accuracy for other, unseen events. Our testing has not revealed any particular weakness of the GA for load events, so these results might hint that the reduced model is not capable of perfectly reproducing the correct response for all events, at least with standard controller models.

3.2. Baden-Württemberg transmission grid

The second model for the evaluation is a transmission grid model of the German state of Baden-WÃ¼rttemberg (BW), comprising the 380 kV and 220 kV level. A geographic representation of the model is shown in Fig. 4. This region consists of the two control zones that form the area of interest (AoI) and the external system for this evaluation, respectively. The reduced model equivalent is obtained by applying the TPNR method [16] to the red zone. This static reduction reduces the number of synchronous machines in the external area by 20 without considering the dynamic behavior of the system. An overview of the main system components is provided in Table 2. The original model uses varying governor models, depending on the power plant type: GAST for gas turbines, HYGOV for hydropower plants, and IEEE G1 for others. Otherwise, the generators all use the same simplified excitation system (SEXS) and IEEE PSS2A. As described in Section 2.1, this information on the controllers used in the original model is used to partly initialize the first generation of the genetic algorithm. To assess the system behavior of the reduced model, we define the following three simulations:

1. A three-phase short-circuit from 1 s to 1.1 s with 0.01 Ω at a bus in the substation marked with the lightning symbol in Fig. 4.
2. A 200 % load step increase at 0.2 s at the substation marked with *L*.
3. A switching event of the line marked with *S*, disconnecting the line at 0.2 s and reconnecting it at 1.2 s.

Due to the size of the BW model, we increase the population size N_P to 100, allowing for more stable solutions in the initial population. Utilizing the information on the controls of the original generators helps to increase the chance of finding suitable configurations in the initial population. Thus, we initialize half of the first population using the controller information provided by the TPNR method and the other half

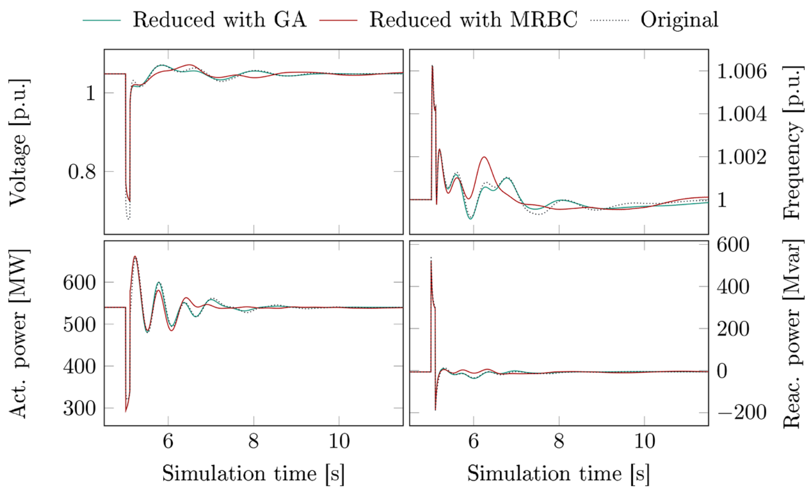


Fig. 3. The system response to the short-circuit with variables of boundary *Bus 02* in the top row and generator *G 08* in the bottom. The model optimized by the GA accurately approximates the original, outperforming the MRBC solution clearly.

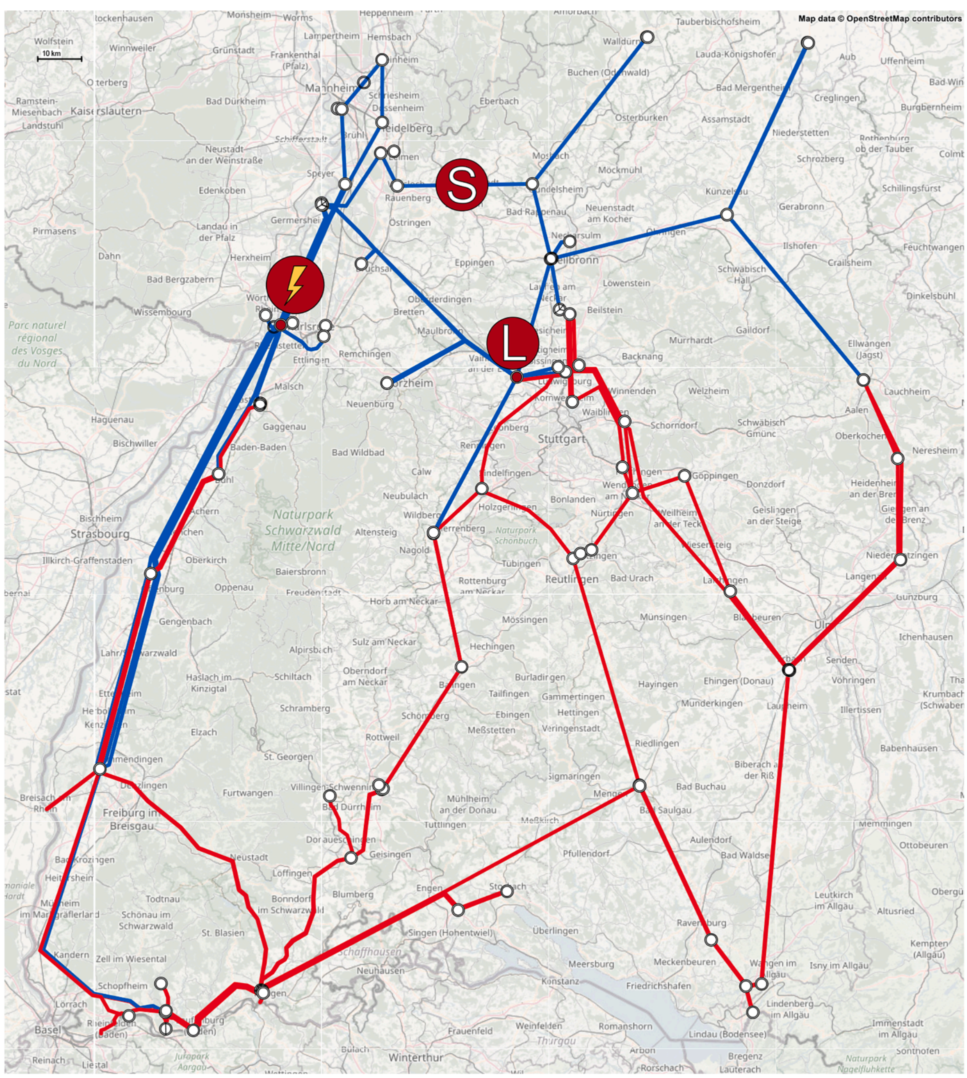


Fig. 4. A geographic representation of the BW transmission grid model consisting of the 380 kV and 220 kV level with the AoI (blue) and the external system (red), which is reduced with the TPNR method [16]. The red symbols indicate the locations of the events used to describe the system behavior.

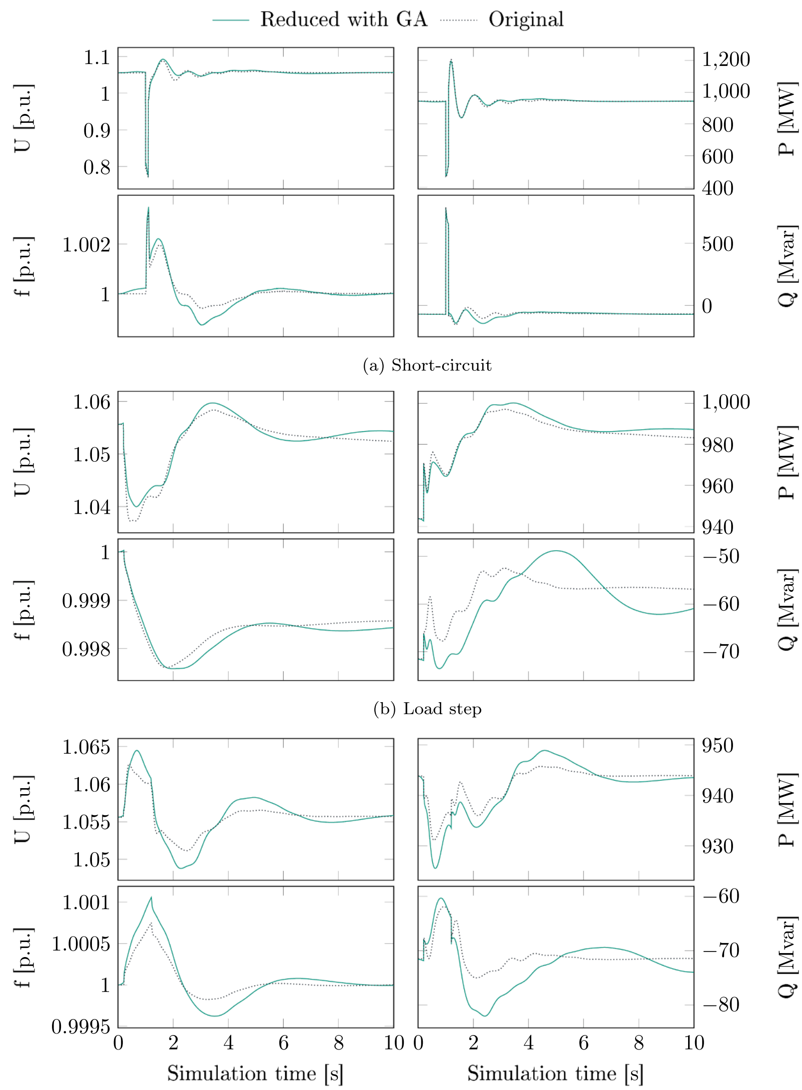


Fig. 5. Qualitative results of the BW model simulation: The left side shows measurements at a boundary bus, and the right of a generator in the AoI.

of the first population completely at random. Working with the model, we find that it is beneficial to first run the GA without any simulation events and subsequently fine-tune the last population of this procedure by optimizing for multiple events. Thus, we first perform 50 generations of optimization without events to find stable controller configurations and then follow with another 50 generations with less aggressive genetic parameters to not alter the presumably already good solutions too drastically. Specifically, the parameter set ($p_c = 0.2$, $p_m = 0.2$, $p_{tm} = 0$, $s_m = 0.1$) is selected to disable the type mutation of controllers and limit all other genetic variation.

The quantitative results of the case study, listed in Table 3, show a similar picture as in the benchmark evaluation: voltages, frequencies, and active power output of the generators are matched with a very high accuracy. The reactive power shows a bigger error. The corresponding response curves for selected variables of the optimizations provide a sense for the approximation quality and are presented in Fig. 5. These plots reveal that the initial responses to the simulated events and the last seconds of the simulations are close to the original model. The optimized equivalent approximates the original BW model almost perfectly after 6 s to 7 s of simulation time and exhibits only small deviations in the first seconds after the simulated events, which should be negligible for many applications.

Table 3
The quantitative results of the BW model simulation show an excellent fit for the voltage, frequency, and active power curve. The deviations in the reactive power are comparable to those in the benchmark system.

	$MAPE_{B,u}$ [%]	$MAPE_{B,f}$ [%]	$MAPE_{G,P}$ [%]	$MAPE_{G,Q}$ [%]
Short-circuit	0.2269	0.0172	0.3678	15.5044
Load step	0.0919	0.0118	0.2278	8.3567
Line dis-/connect	0.0880	0.0098	0.1859	3.7019

Counterintuitively, the reduced number of components in the model does not necessarily translate to faster calculations in PowerFactory, as shown in Table 4. While the short-circuit simulation benefits massively from the reduction, the load step is actually slower with the reduced model. For this simulation, the original model produces smoother curves with less high-frequency changes for the monitored system variables. This likely enables PowerFactory to calculate with larger time steps, enabling a faster simulation.

Table 4
The time to simulate each event in the BW model for 120 s. While the reduction can significantly decrease simulation times, there is no guarantee.

	Original	Reduced	Difference	Rel. diff.
Short-circuit	412.09 s	256.17 s	−155.92 s	−37.8 %
Load step	42.85 s	49.98 s	+7.13 s	+16.6 %
Line dis-/connect	46.98 s	51.45 s	+4.47 s	+9.5 %
Total	501.92 s	357.6 s	−144.32 s	−28.8 %

4. Discussion

In this section, we discuss the advantages and limitations of the proposed parameter optimization for reduced equivalent models. The proposed method achieves a good approximation for the simple IEEE benchmark system, as well as for the complex and more detailed BW transmission grid model with hundreds of nodes. The observed errors for most variables are well in the acceptable range defined in Section 3. However, optimizing the system behavior to fit the response to certain selected events, does not give any guarantees for the behavior and accuracy of the reduced equivalent model. Specifically, the proposed GA-based optimization exhibits imperfections approximating the reactive power of the retained generators. There are several possible explanations for the difficulty of approximating the reactive power output. First, note that the reactive power highly depends on the voltage at the buses close to the retained generators. In Fig. 5, for example, it can be observed that even slight overvoltages correlate with more pronounced negative reactive power errors, and vice versa. A second potential source for errors are the reactive power outputs of the aggregated generators in the external systems. These might have difficulties replicating the reactive power response of the original generators in the external system for two reasons: (1) the aggregated controllers might lack the fidelity to reproduce the detailed response, and (2), these generators themselves highly depend on local voltages, which are usually not preserved in the external system since the reduction methods focus on the boundary voltages. While a definitive answer to the source of these mismatches will require a deeper investigation, these potential sources of errors do not hint at an inherent problem of the GA-based optimization. Overall, the evaluation demonstrates that the proposed control optimization can be combined with different static reduction methods to fit the needs of the use case at hand. In comparison with similar existing works [8,9], the proposed method significantly improves several key aspects:

- In contrast to existing works, our proposed method includes PSSs in the optimization.
- Instead of a custom control structure in the form of weighted sums of transfer functions to represent the controllers, we only utilize standard controller models for improved compatibility with simulation software.
- While the referenced works only optimize the parameters of the previously mentioned weighted transfer functions, our proposed method also includes the selection of controller models in the optimization process.
- The proposed method is agnostic to the static reduction method, as demonstrated by using two distinct methods in the evaluation.

Table 4 shows that the reduction does not always result in faster simulation times using PowerFactory. However, depending on the specific model and simulation, the reduction can significantly reduce the simulation times. Additionally, reducing the number of components can be the deciding factor to enable real-time simulation, as real-time simulators, such as RTDS, have a fixed capacity that supports a limited number of components.

While the proposed method yields promising results, the parameter optimization is currently limited to three controller types for synchronous machines. However, with an increasing share of generation from renewable energy sources, inverter-based generation and the corresponding control become an increasingly important factor in the dynamic system behavior.

5. Conclusion and future work

In the present work, we propose a new genetic algorithm (GA) for the optimization of synchronous machine controls in statically reduced network equivalents to approximate the behavior of their detailed counterparts. The GA is based on novel genetic operators specifically designed for synchronous machine controls, including a flexible representation, crossover, and mutation. Our method can be combined with static reduction methods, such as REI [4] and TPNR [16] to create models with a reduced complexity for dynamic simulations. We combine our optimization method with both of these static methods and evaluate these combinations with a simple benchmark system and a complex, real-world transmission grid model to cover a realistic use case of the method. The method is evaluated against a system-knowledge-based Manual Rating-based Configuration (MRBC) solution.

For further developments, the optimization method itself could be enhanced by utilizing more sophisticated techniques, such as adaptive mutation and crossover probabilities, adaptive completion criteria, and the newer NSGA-III genetic algorithm [26]. Currently, the proposed optimization method is limited to a small set of synchronous machine controller models. Including more common controller models and even extending the method to other types of controllers, e.g., for converters, broadens the applicability and accuracy of the method. The identified imperfections with approximating the reactive power might be mitigated by weighting factors for the fitness function and selecting the best solution. This could also be useful to tweak the performance for applications that focus on certain variables. The heuristic nature of the proposed method does not give any guarantees regarding the accuracy of the optimized reduced model. Thus, a systematic approach for the definition of events and automatic reporting could help gain insights into model accuracy and limitations, leading to increased confidence in the model.

Overall, the optimization method introduced in this work can be paired flexibly with different static model reduction techniques, enabling dynamic simulations of models for a wide range of use cases. This flexible combination of methods allows preserving critical geographic information for models with high shares of renewable energy sources. The method demonstrates promising results in a real-world case study and does so using standard models only, ensuring broad compatibility with modeling tools.

CRediT authorship contribution statement

Moritz Weber: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Conceptualization; **Hüseyin K. Çakmak:** Writing – review & editing, Supervision, Funding acquisition; **Uwe Kühnapfel:** Writing – review & editing, Supervision, Funding acquisition; **Veit Hagenmeyer:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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