Simulation-based Parameter Optimization Framework for Large-Scale Hybrid Smart Grid Communications Systems Design

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***Abstract*—The design of reliable, dynamic, fault-tolerant hybrid smart grid communication networks is a challenge to achieve for autonomous power grids. A simulation-based parameter optimization framework is proposed to tune parameters of hybrid communication technologies to achieve the optimal network performance. It consists of three main components: a parallel executor used to speedup a list of simulations; a sampler running simulations with all possible parameter sets for the input parameter variables by using the parallel executor at each generation; and a hybrid stochastic optimization algorithm for tuning configurable parameters of hybrid designs and application parameter variables. The proposed hybrid metaheuristic optimization algorithm combines an evolutionary algorithm with a gradient method to quickly achieve an approximate globally optimum solution. Three optimization test functions are employed to train the adjustable parameters of the hybrid algorithm. Results show that the proposed parameter optimization framework helps the designer to choose the right hybrid architecture with an optimal parameter set for a large-scale broadband PLC-WiMAX hybrid smart grid communication network.**

I. Introduction

The power grids worldwide are evolving into smart grids by adding intelligence to the operation and control of the system[1], [2], [3]. As a result, it becomes increasingly important to explore the communication capabilities of different types of smart grid topologies [4], [5]. The envisioned smart grid communication network for distributed applications broadly consists of Home Area Networks (HAN), Neighborhood Area Networks (NAN), and a Wide Area Network (WAN), and it is expected that a variety of communication technologies will be utilized in the hybrid communications systems infrastructure [6]. The design of hybrid communication networks are not straightforward, because the different technologies used in different sub-network have a large number of configurable parameters which increases the amount of experimental (or simulation) tests necessary for their evaluation. The non-deterministic nature of the environment is another factor which makes network design difficult. The hybrid smart grid communication network must be fault tolerant and adaptive because of the dynamic network topology caused by dynamic power grid topology and changing objectives of different smart grid applications.

The design of a hybrid smart grid communication network requires a simulation-based optimization method to tune the configuration parameters of communication technologies and parameters of smart grid applications. A simulation-based parameter optimization framework is proposed in this paper to help the designer choose the right hybrid architecture with an optimal parameter set. This scalable and extendable framework may accept different communication technologies on top of different topologies, and identify the optimal configurable parameters for each related communications model and application parameters for that hybrid design.

The novel contribution of this work is the simulation-based parameter optimization framework with features of parallel computing and using a hybrid evolutionary search algorithm. The proposed design provides a simulation-based optimization tool than can help designers identify the optimal parameter set for a selected hybrid communication configuration. Although the hybrid evolutionary search agorithm has previously been investigated in [7] and [8], this algorithm is utilized in this paper to develop a new tool that performs network parameter optimization. While there has been similar previous work done to simulate hybrid communication networks as in [9] and [10], the proposed algorithm has been designed specifically to be used with NS3. NS3 is an open-source discrete-event network simulator capable of simulating many important aspects of communication technologies: such as propagation model, spectral model, payload modulation coding scheme, and service flow type [11]. Using the simulator, the optimization algorithm tunes all the input parameters, at both the application and architectural level, to provide an optimum set within the required QoS metrics. The large parameter space and the simulation-based genetic algorithm impose a heavy computational load. It is beneficial to parallelize execution of these computationally intensive simulations and thus speed-up the performance of the simulation-based optimization algorithm. Through combining a gradient-based algorithm and a genetic algorithm, the hybrid evolutionary gradient algorithm is proposed as a new parameter identification algorithm. The primary application of this framework is thus the optimization of network configuration parameters and application parameters through extensive hybrid communication system simulations. The proposed solution provides a way to design and optimize hybrid smart grid communication systems in a highly non-deterministic environment for a large number of cooperating intelligent power grid devices.

II. NS3-based Hybrid Smart Grid Communication Networks

NS3 can be set to operate in many different modes [11]. In deterministic mode, it will produce replicable results while testing the application. In probabilistic mode, it will also simulate the non-deterministic nature of the the communication channel and the low-level communication protocols of a variety of communication technologies. It can be used to test communication technologies, protocols, and algorithms through the performance metrics of the designed smart grid network architectures and applications. It also can incorporate an arbitrary number of Photovoltaic (PV), smart meter and data concentrator communication nodes, on arbitrary topologies and it allows to implement the customized applications such as settings of packet size and data rate

A suite of hybrid smart grid communication system simulations using NS3 have been developed for distributed smart grid application [6]. NS3 was chosen because of its popularity, open-source nature, and the existing availability of models for numerous networking functionalities. In the envisioned hybrid smart grid communication networks, the Home Area Network (HAN) considers the LoWPAN and PLC technologies, the Neighbor Area Network (NAN) can choose WiFi, WiMAX, and Ethernet cable, while the wide area network is assumed to employ optical cables. The corresponding NS3 modules of these alternative technologies can be configurable with multiple parameters. Referring to the initial manual verification results shows that both broadband PLC (BPLC) and WiMAX models have more variable parameters with high impacts on the designed system's performance[6]. Thus, the hybrid BPLC-WiMAX design is considered to verify the efficacy of the proposed parameter identification framework. Table I lists all configurable parameters of both BPLC and WiMAX NS3 models. The spectrum model of BPLC has three adjustable parameters: low-bound frequency, high-bound frequency, and number of channels. [6], [11], [12] provide a detailed description of the other parameters.

Similar to the core NS3 modules for different technologies, the smart grid application layer may also be parameterized. Two commonly used application parameters considered in designing smart grid applications are the packet size and data rate of PV measurement or curtailment control signal messages. Thus, the purpose of tuning adjustable parameters of hybrid designs is to search out optimal configurations of different communication technologies and optimal parameters for the distributed smart grid applications. The expected optimization algorithm is built around the NS3 simulator and it calls the simulator with the configurable parameter set of network models and applications.

III. Simulation-based Parameter Optimization Framework

The framework for this tool was designed to utilize three main components. It consists of a parallel executor wrapped inside a sampler, which itself is wrapped inside the hybrid optimization algorithm. The core module of the design is the parallel executor, which also processes the raw results. The list of simulations to run is provided by the sampler which simulates all scenarios required by the optimizer algorithm for a single generation. It also handles data storage, additional post-processing, and initial comparison of the results. The optimizer algorithm determines which simulation scenarios are required to be tested and provides them as a list of parameters to the sampler. The high level block diagram of this framework is provided in Figure 1

TABLE I
Configurable Parameters of the BPLC-WiMAX Hybrid Design

Model	Parameter	Values
BPLC	Low frequency	$1-2$ (MHz)
	High frequency	$3-100$ (MHz)
	Channel number	$100-1200$
	Payload modulation coding scheme	QAM64_rateless, QAM32_rateless, QAM4_rateless, QAM64_12_21, BPSK_1_2, BPSK_rateless
	Header modulation coding	BPSK_1_2, BPSK_1_4
WiMAX	Phy layer modulation	QAM16-12, QAM16-34, QAM64-32, QAM64-34, BPSK-12, QPSK-12, BPSK-34
	Service flow	UGS, RTPS, NRTPS, BE
	Propagation model	Friis, Cost231, Random, Log
	Scheduler	SIMPLE, MBQOS, RTPS
Application	Data rate	$16-56$ (Kbps)
	Packet size	$64-2048$ (Bytes)

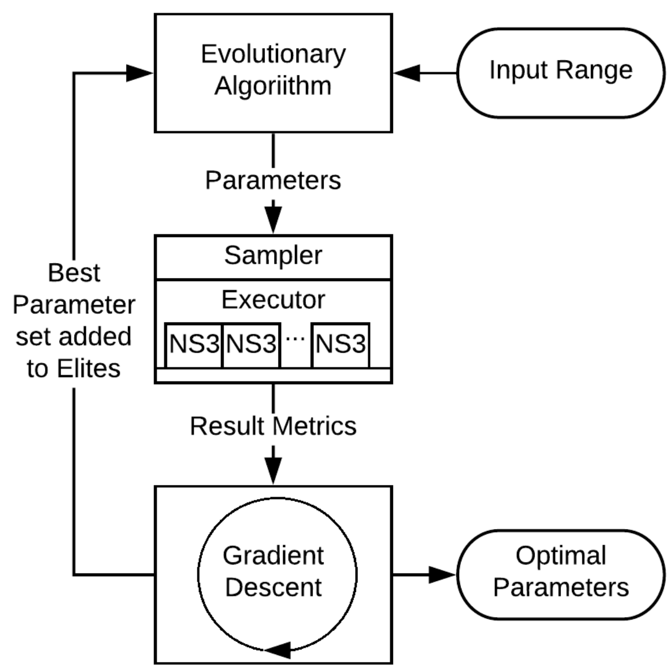

Fig. 1. High-Level Framework Block Diagram

A. Parallel Executor

The purpose of the parallel executor is to run a large number of simulations in parallel by using the ubiquitous multicore physical or virtual processors available to most systems, and it has been implemented using the "concurrent.futures" and "multiprocessing" modules in python. It may also be extended using the mpi4py module to take advantage of highly scalable cluster computing resources. The parallelism and scalability of this parallel executor allows for greatly improved computational time by efficiently utilizing all available computational resources.

B. Sampler

Three critical system design requirements are considered to validate the performance of each hybrid communications design, and they are a single trip latency of 300 ms or less, throughput of 9.6 Kbps or more, and packet loss rate of 1% or less [6]. To further quantify the performance value of different parameter settings and to better compare similar cases, a weighted cost function is proposed [13] as below,

$$cost = \sum_{i=1}^{3} w_i * x_i + CC_i$$
$$\text{where} \quad CC_i = \begin{cases} 10000 & x_i \geq lim_{i+} \\ 0 & lim_{i-} < x_i < lim_{i+} \\ 10000 & x_i \leq lim_{i-} \end{cases} \tag{1}$$

where x_1 is latency, x_2 is throughput, x_3 is packet loss rate, and $w_i, i = 1, 2, 3$ is the weight factor of the i^{th} metric, which is the product of importance factor of this metric relative to the other metrics and the unit factor of this metric. In this paper, three corresponding weight factors are set as $w_1 = 1000, w_2 = 0.001, w_3 = 20$. $CC_i, i = 1, 2, 3$ refers to the conditional costs of the i^{th} metric which allow setting predefined conditional limits, such as boundary conditions of this metric $[lim_{i-}, lim_{i+}]$. Thus, using these conditional costs, the out-of-bounds regions of these metrics result in a very high cost which effectively restricts the optimization algorithm to search for results within the specified boundary of these metrics.

C. Hybrid Evolutionary Gradient Algorithm

To identify the optimal parameter set for the specific hybrid communications system design, there are two commonly-used algorithms namely, gradient descent and evolutionary algorithms [14], [15]. Similar to hill climb algorithms, the gradient-based algorithms perturb an initial guess along all available degrees of freedom to improve the objective function value, and the best perturbed position becomes the new position at each iteration, until no perturbation can improve the objective. Meanwhile, the evolutionary algorithm is a selective random search algorithm designed to achieve a global optimum within a large parameter space[16]. The general idea of many variants of these algorithms is to identify dominant solutions and to breed these solutions until the global optimum is found. There is a finite chance for mutation of each parameter every time a new solution is bred. Only the best solutions are retained in the breeding population as the elite population. Both populations are limited in size so as to reduce the overall computational requirements.

To take advantage of both the quick optima identification ability of the gradient-based algorithm and the broad optima search ability of the evolutionary algorithm, the hybrid algorithm is proposed in this paper. This hybrid approach allows the algorithm to initially perform a broad search along the parameter space using a fixed population size with random mutations and elites and then quickly narrow down on the optimum by performing a gradient descent. In this way, the hybrid algorithm consists of the following three steps: Step 1. the evolutionary algorithm is executed first for each generation; Step 2, if a new optimum is found, the gradient algorithm is executed with this solution as the initial guess; Step 3, If the gradient descent algorithm identifies a more optimal solution, the new solution is added to the breeding population for the next generation. This leads to the algorithm quickly finding local minima and breaking out of them over multiple generations. The simulations are run using the sampler. The sampler firstly builds a list of simulation commands using a set of adjustable parameters and their available values in the master processor. Then, the sampler runs the parallel executor to execute these simulations in all available slave processors in parallel. Finally, the master processor continue to post-process the simulation results including evaluating their performance values through the above proposed weighted cost function, and sorting them into different categories. The detailed hybrid optimization algorithm is listed in Algorithm 1. $ExecutorPool$ refers to the pool of workers which is maintained by the parallel executor. $BestHash$ holds the hash of the simulation result with the lowest cost so far. $Position$ refers to the initial parameter set the gradient algorithm perturbs. $MaxPop$ is the general population size. $PopList$ refers to the population used to breed $Values$ for the next generation. Simulated annealing is implemented using a random chance to use the general population in $Results$ to breed the next generation instead of $Elites$.

IV. Optimization Test Functions

To validate the performance of the above proposed parameter optimization framework, many different types of test functions have been used to benchmark the optimization algorithm [17]. For the comparison purpose, the Rastrigin, Eggholder, and Rosenbrock functions were selected specifically due to their different natures which pose different challenges to the optimization algorithm design in this paper.

1) Rastrigin function: It features with the periodic nature and a distinct global optimum, and has a global minima at (0,0) with many, evenly spaced, local minima surrounding it, and defined in Equation (2):

$$f(x_n) = 10n + \sum_{i=1}^{n} (x_i^2 - 10cos(2\pi x_i)) \tag{2}$$

where n is the number of input variables, x_i is the i^{th} input variable. These notation are applied for the rest two functions.

2) Eggholder Function: This function has a distinct global optima with a more pseudo-random arrangement of the local minima surrounding it. It is given by:

$$f(x) = \sum_{i=1}^{n-1} [-x_i \sin(\sqrt{|x_i - x_{i+1} - 47|}) - (x_{i+1} + 47) \sin(\sqrt{|0.5x_i + x_{i+1} + 47|})] \tag{3}$$

Algorithm 1 Hybrid Evolutionary Gradient Algorithm

```
(Parameters, Values) ← GetParamVals(script)
Evolutionary algorithm starts
for gen = 0 to maxGen do
    Run Sampler with ExecutorPool
    for Result from ExecutorPool do
        parse Result into ParsedResult
        obtain Hash of ParsedResult
        store ParsedResult with Hash as the key
    end for
    BestHash ← hash(min(cost(Elites))),
    Position is obtained from values of BestHash
    Gradient algorithm starts
    while Position has changed do
        Perturb Position to (Parameters, Values)
        Run Sampler with ExecutorPool
        for Result from ExecutorPool do
            parse Result into ParsedResult
            obtain Hash of ParsedResult
            store ParsedResult with Hash as the key
        end for
        if min(cost(Elites)) < cost(BestHash) then
            BestHash ← hash(min(cost(Elites)))
            obtain new Position from new BestHash
        end if
    end while
    Gradient algorithm ends
    Preparation of the next generation starts
    Limit population of Elites and Results
    PopList selected as Elites or Results
    clear Values
    for ParentA in PopList do
        select different ParentB from PopList
        for j = 0 to Length(Position) do
            breed traits of ParentA and ParentB
            add child traits to Values
        end for
    end for
    Preparation of the next generation ends
end for
Evolutionary algorithm ends
return Results(hash(min(cost(Elites))))
```

3) Rosenbrock Function: It features a distinct global optimum within a long valley and one optimal solution at (1,1). It shows very little variation across a wide range of the input parameters, and is defined as:

$$f(x_n) = \sum_{i=1}^{n-1} (100(x_i^2 - x_{i+1})^2 + (1 - x_i)^2) \tag{4}$$

In this paper, three test functions were designed to accept 2 numerical and 2 non-numerical input parameters to more accurately model the NS3 simulation environment for the hybrid communication design of smart grid. To ensure that the expected global optimum is within the range of the inputs, three functions are scaled or offset as required.

TABLE II
COMPARISON OF DIFFERENT OPTIMIZATION METHODS

Optimization Method	Failure Rate (%) (Average Failure Cost)		
	Rosenbrock	Rastrigin	Eggholder
Evolutionary	8.44 (8.493)	11.09 (8.3148)	10.16 (7.8154)
Gradient	95 (113930)	93.33 (141430)	95 (131800)
Hybrid	4.69 (6.05)	7.03 (6.0889)	6.02 (6.1299)

V. EXPERIMENTAL SIMULATION AND RESULTS

A. Reference Test Case A

The taxonomy feeder titled R2-25.00-1 [18] with 1080 nodes, referred to as Reference Test Case A (RTC-A), has been selected to perform the validation of the developed parameter identification platform. The detailed construction of this test case is provided in [6]. The subsequent communication infrastructure of RTC-A consists of 57 PV inverters, 275 smart meters, 10 data concentrators, and one edge router. It is divided into 10 subareas based on the location of 10 data concentrators. The BPLC-WiMAX hybrid communications design is simulated with a large set of configurable parameters of two communication models in the NS3 simulator on top of the RTC-A.

B. Verification of Metaheuristics Optimization Algorithms

Using the three above described optimization test functions, the purpose is to verify the training parameters of the proposed hybrid optimization algorithm. The training parameters considered in this paper are mutation rate (MR), mutation chance (MC), and maximum elites (ME) of the evolutionary algorithm, and the step size (SS) of the gradient descent algorithm. The mutation rate defines the maximum extent of a single mutation as a percentage of the parent trait, mutation chance is the percentage probability of a mutation occurring, and maximum elites is maximum size of the elites as a percentage of the total population. Increasing step size decreases the number of gradient descent steps that will be performed and hence only impacts computation speed. The resulting performance comparison using the two metrics of average failure cost and failure rate is conducted as below.

1) Performance Comparison of Three Algorithms: The performance of three optimization algorithms: gradient, evolutionary, and hybrid algorithms are compared in Table II. The failure rate is defined as the percentage of cases where the algorithm fails to identify the global optimum. The average failure cost is calculated as the average distance of the found solution to the global optimum upon failure. The genetic algorithm performance, shown in the first column of Table II, indicates that the evolutionary algorithm is capable at determining the optimal solution on its own. There is certainly room for improvement, however. The failure rates and costs of the gradient descent algorithm are very high, as shown in Table II. This indicates that gradient descent alone is not a good method for identifying the optimum solution in such cases. As expected, the verification results show that the hybrid algorithm has improved performance compared with either the evolutionary or gradient descent algorithm individually.

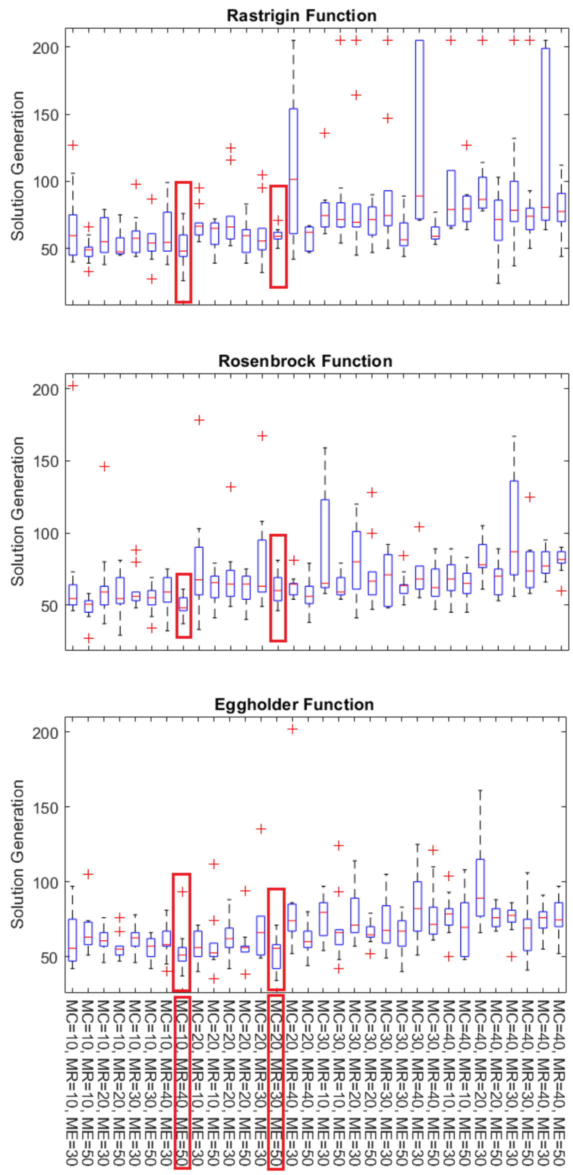

Fig. 2. Comparison of Hybrid Algorithm in terms of Test Functions

2) Performance Characterization of the Hybrid Algorithm: The hybrid algorithm in terms of failure rate and average failure cost has been identified as the best option in the above subsection. The effects of the parameters of this algorithm is further explored using the three different optimization test functions. To perform this analysis, the MC, MR, and ME parameters are varied between 10-50% in intervals of 10%. The results are shown in Figure 2. For each blue box plot, the central mark indicates the median of solution generation, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. Also the red cross indicates the lowest and highest outliers.

For the Rastrigin function, the result shown as the left red highlights in Figure 2 indicate that the best results can be achieved when the mutation chance is as low as 10%, the mutation rate is 40%, and the maximum elites is 50%. The effect of these parameters is not as large as the effect of the size of the elites list. This conclusion is derived from the fact that with higher mutation chances, the performance is still acceptable as long as the number of elites is 50%. This indicates that the optimizer is able to search the breadth of the function across the input variable range, however it has difficulty narrowing down to the optimal solution unless supported by a bigger elite list and lower mutation chance. The average solution generation is the same or lower for all cases in this hybrid scenario compared to the genetic algorithm. This definitively indicates the benefit of implementing this hybrid algorithm for these types of functions.

For the Rosenbrock function, the blue box plot indicates that the best results are achieved when mutation chance=10%, mutation rate =40%, and maximum elites=50% as shown in the left red highlights in Figure 2. The results do not indicate as much of an impact of these parameters on the solution generation, compared to the other two test functions. This indicates that although the parameters have some effect, the overall effect of these parameters does not have as large an impact on the solution generation. This may be attributed to the fact that the function has a large valley handled by the gradient descent portion of the algorithm.

For the Eggholder function, the box plot indicates that the best results are located when the mutation chance is 20% , the mutation rate is 30%, and the maximum elites is 50%, as shown in the right red highlights of Figure 2. Comparing to the Rastrigin function, the best performance is achieved with mutation chance=20%, not 10% and mutation rate=30% instead of 40%. This indicates that the optimizer is able to search the full width of the input variable range, however it has difficulty narrowing down to the optimum. Thus, this function requires more aggressive mutation to avoid getting trapped in a local minimum.

From these results, it may be concluded that a setting of mutation chance=10%, mutation rate=40%, and maximum elites=50% will result in good performance across wide variety of test functions or applications. These settings of the proposed hybrid optimization algorithm are applied to tune the parameters of the NS3-based hybrid smart grid communication system design.

C. Parameter Identification Results

The proposed hybrid optimization algorithm takes both numeric and non-numeric configurable parameters. The BPLC-WiMAX hybrid design to be tested has the configurable parameters shown in Table I. The optimal parameters as identified by the proposed parameter optimization framework are summarized in Table III. It is worth noting that the optimal parameters of communication technology modes, namely BPLC and WiMAX models, are almost coincident with the initial manual results of [6].

A small portion of optimal cases as determined by the optimizer for the BPLC-WiMAX hybrid design are shown in Table V. Compared with the optimal cases identified by the sampler in Table IV, the optimizer results have higher granularity. To achieve this set of optimal cases, the trade-offs made by the optimizer are apparent in observing the parameter values used. Depending upon which trade-offs made by the optimizer are acceptable, the user has the option of selecting from a large set of options, the size of which is determined by the maximum elites parameter. It is noticeable that the optimizer pushes the data rate as high as it can while simultaneously optimizing the packet size for low latency and packet loss rates. This is exactly the behavior needed from the optimization framework.

From these results it is clear that the optimizer works well in achieving the best possible network configuration within the given range of parameters.

TABLE III
OPTIMAL PARAMETERS OF THE BPLC-WIMAX HYBRID DESIGN

Model	Parameter	Values
BPLC	Low frequency	2 (MHz)
	High frequency	3 (MHz)
	Channel number	1146
	Payload modulation coding scheme	QAM64_rateless
	Header modulation coding	BPSK_1_2
WiMAX	Phy layer modulation	QAM16-12
	Service flow	Best Effort
	Propagation model	Friis
	Scheduler	SIMPLE
Application	Data rate	55.98 (Kbps)
	Packet size	66 (Bytes)

TABLE IV
RESULTS OF SAMPLING SIMULATED CONFIGURATION

Throughput (kbps)	Latency (ms)	PLR (%)	DR (bps)	Size (B)
55.979	6.832	0.057	56000	64
55.884	10.466	0.213	56000	128
55.993	17.923	0.027	56000	256
55.962	34.183	0.098	56000	512
56.016	64.539	0.031	56000	1024
55.91	129.253	0.296	56000	2048

TABLE V
OPTIMAL RESULTS FOR SIMULATED CONFIGURATION

Throughput (kbps)	Latency (ms)	PLR (%)	DR (bps)	Size (B)
55.937	5.512	0.074	55978	66
55.959	5.649	0.034	55980	66
55.977	5.661	0.035	55997	66
55.979	5.562	0.035	55999	67
55.979	5.487	0.057	56000	66
55.859	5.564	0.034	55880	68
55.971	5.612	0.055	55998	68
55.948	5.571	0.056	55973	66
55.964	5.472	0.038	55985	64

VI. CONCLUSION

This paper focuses on the development of simulation-based parameter optimization framework to identify the optimal configurable parameters of different communication technologies and application parameters for the large-scale hybrid smart grid communication system design. From the validation results, we have the following key findings: 1) the proposed hybrid evolutionary search optimization algorithm can improve convergence speed compared to the single gradient or genetic algorithm. 2) the optimal parameter set of the BPLC-WiMAX hybrid design is successfully identified by the proposed algorithm. The best data rate is set to 55.98 Kbps and the optimal packet size is set to 66 bytes. The parameters may be set and any further network analysis now performed with confidence that the system has been optimally designed. Planned future development for this tool includes adding topology optimization capabilities and adaptive tuning of the optimizer parameters.

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