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Evaluation of a New Parallel Numerical Parameter Optimization Algorithm for a Dynamical System

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Abstract. It is important to have a scalable parallel numerical parameter optimization algorithm for a dynamical system used in financial applications where time limitation is crucial. We use Message Passing Interface parallel programming and present such a new parallel algorithm for parameter estimation. For example, we apply the algorithm to the asset flow differential equations that have been developed and analyzed since 1989 (see [3-6] and references contained therein). We achieved speed-up for some time series to run up to 512 cores (see [10]). Unlike [10], we consider more extensive financial market situations, for example, in presence of low volatility, high volatility and stock market price at a discount/premium to its net asset value with varying magnitude, in this work. Moreover, we evaluated the convergence of the model parameter vector, the nonlinear least squares error and maximum improvement factor to quantify the success of the optimization process depending on the number of initial parameter vectors.

INTRODUCTION

In this paper, we study parallel optimization with initial parameter vector (IPV) pools related to nonlinear dynamical systems and present a numerical parameter optimization algorithm. A serial algorithm called the asset flow optimization forecast algorithm was prepared and an inverse problem having parameter optimization for the asset flow differential equations (AFDEs) has been used for a set of stocks in the set of closed-end funds (CEFs) traded on the NYSE (see [5]). The optimization algorithm contains a quasi-Newton (QN) weak line search [1-2] and a semi-dynamic initial parameter pool [5]. Daily market prices (MPs) and net asset values (NAVs) are used to find the parameter vectors in the AFDEs via curve fitting for the previous n days without knowing the reference functions explicitly. Runge–Kutta (RK4) method is employed to solve the dynamical system numerically and a nonlinear least-squares (NLS) technique with initial value problem approach is applied based on the MP variable.

There is no algorithm that will warranty the number of required iterations to obtain the region of the global optimum (see [7, Chapter 23]). In order to deal with this challenging problem in different financial market situations, we need adequately large number of IPVs generated by suitable methods and incorporated in the optimization process via high performance computing using Message Passing Interface (MPI) parallel programming. It may take several days to run the sequential code in order to obtain optimal parameters with large number of IPVs to be used for stock price forecasting. When the parallel programming is used, the total time to obtain a high quality parameter vector will be reduced and this may be useful for a trader using daily closing prices. Moreover, it is important to measure the role of large number of IPVs on the success of the optimization.

We use MPI parallel programming and analyze the success of the optimization process depending on the number of IPVs for a new parallel hybrid algorithm to estimate the model parameter vectors. Duran and Tuncel [10] tested for 64, 128, 256 and 512 cores on the Ege Server (see [9], HP ProLiant BL2x220c G5 Blade) using the 512 IPVs. They obtained speed-up for the simulated MP and NAV time series of length 1000 to run up to 512 cores. Unlike the project report [10], we deal with more extensive financial market situations and analyze the convergence of the model parameter vector, the NLS error and maximum improvement factor (MIF) to measure the success of the optimization process depending on the number of IPVs and the number of CPU cores. Moreover, we examined the

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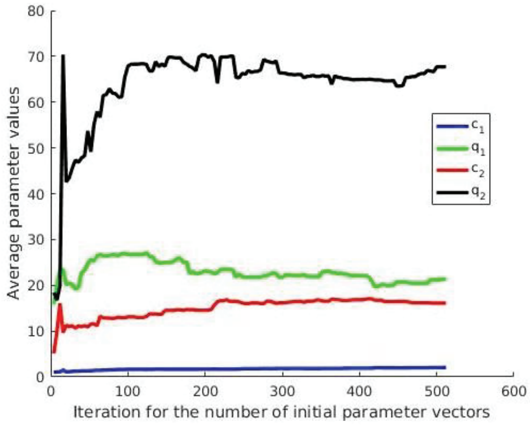

FIGURE 1. The convergence diagram of the model parameters for the curve fitting via Monte Carlo simulation using 1k_v8 as the number of IPVs increases up to 512.

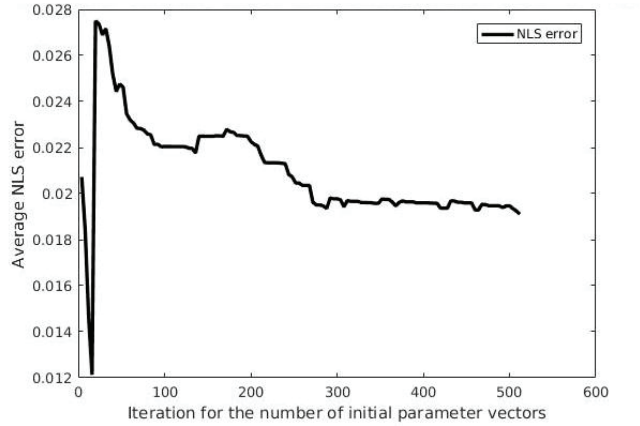

FIGURE 2. The convergence diagram of the NLS error for the curve fitting using 1k_v8 by Monte Carlo simulation as the number of IPVs increases up to 512.

behavior of the time series of length 500 and 2000. We achieved speed-up to run up to 512 cores.

The remainder of this work is organized as follows: First, we use the parallel nonlinear parameter optimization algorithm with classified IPV pools described in the project report [10], with new design of experiments. We use the 3rd version of AFDEs and the related problem constraints (see [4] and [11]) in this paper. The convergence results of the numerical parameter optimization depending on the number of IPVs and the role of volatility are discussed. Finally, we conclude this work.

CONVERGENCE RESULTS OF THE PARAMETER OPTIMIZATION DEPENDING ON THE NUMBER OF IPVS AND THE ROLE OF VOLATILITY

We produce time series pairs as proxy to MP and NAV by using random walk simulation where the volatilities of the time series are similar to that of real CEFs traded on NYSE (see [6] and [8]). Table 1 displays the design and threshold values for the numerical optimization process. Table 2 explains the simulated MP and NAV time series of length 500, 1000, and 2000 with their volatility behavior in terms of standard deviation, price ranges and status of stock MP at a discount/premium to its NAV where P and D stand for premium and discount, respectively. The parameters in Tables 1-2 are chosen by considering the problem constraints, time constraints, available computing resources, and financial feasibility to reflect various financial market situations generating different curves having behaviors such as almost steady, uptrend, downtrend, strong uptrend and strong downtrend in the design of experiment. The problem constraints are discussed in [4], [5], [6] and [11].

Table 2 illustrates the Monte Carlo simulation results for the parameter vector, the average NLS error and the average MIF defined as the ratio of the final NLS error to the initial NLS error. Generally, the smaller MIF corresponds to a better performance, which depends on the proximity of the IPV to the optimal one as well. Fig. 1, Fig. 2 and Table 2 show that the computed optimal parameter values, the average NLS errors, and the average MIF can converge to certain values within corresponding small ranges smoothly, after fluctuations.

We compare the serial algorithm with fixed initial parameter pool having 64 IPVs and the parallel algorithm having 512 IPVs in the classified pool and we obtain smaller NLS errors in Fig. 3 and better MIF in Fig. 4 via the parallel algorithm for the price time series 1k_v6, 1k_v7 and 1k_v8. The better performance in terms of errors of the parallel algorithm compared to the serial one can be explained by the usefulness of larger number of IPVs.

TABLE 1. The computational optimization by finding parameter vector in the AFDE for a large sample data set. QN method with weak line search is applied.

	Event period	**RK4 method step size**	**# of parameter vectors in pool**	**Threshold for the gradient**	**Threshold for the NLS error**
Dataset 1	5	0.05	56	10^{-5}	0.16
Dataset 2	5	0.05	64	10^{-5}	0.16
Dataset 3	5	0.05	≤ 512	10^{-5}	0.16

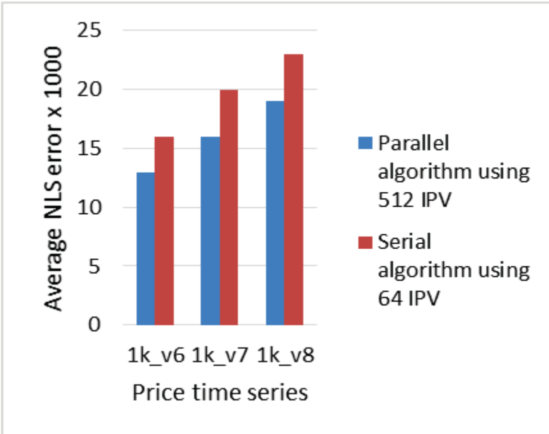

FIGURE 3. The performance comparison of the serial algorithm with fixed initial parameter pool having 64 IPVs versus the parallel algorithm having 512 IPVs in the classified pool, in terms of NLS errors, in Table 2.

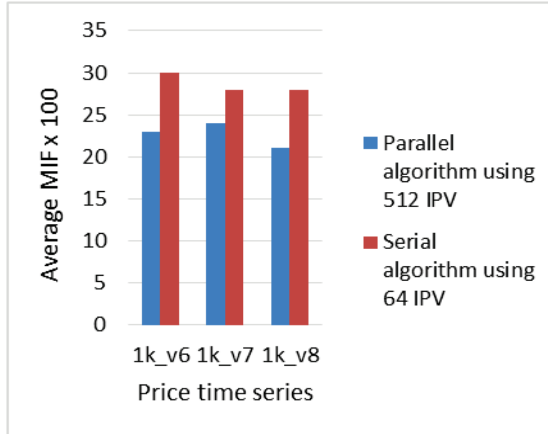

FIGURE 4. The comparison of the serial algorithm with fixed initial parameter pool having 64 IPVs versus the parallel algorithm having 512 IPVs in the classified pool, in terms of MIF, in Table 2.

Moreover, the average NLS error of the time series having relatively high volatility is higher than that of the time series having low volatility in Fig. 5. For example, 0.5k_v1 - 0.5k_v4 versus 0.5k_v5 - 0.5k_v8. In general, the NLS error is larger for the time series of length 1000 as well when the volatility is sufficiently larger for both MP and NAV.

TABLE 2. Description of the time series and Monte Carlo simulation results for various number of IPVs.

Price time series (PTS)	Size of PTS	# of IPV	Volatility ratio (MP / NAV)	MP range [Min – Max]	NAV range [Min – Max]	Status Initial/ Final	Parameter vector c_1	q_1	c_2	q_2	Avr. NLS error	Avr. MIF
0.5k_v1	500	56	11.77 / 5.18	53.60 - 99.00	45.57 - 67.23	P / P	0.97	25.89	7.16	41.38	0.038	0.11
0.5k_v2	500	56	7.53 / 4.23	52.88 - 81.22	54.45 - 78.47	P / P	0.87	44.65	4.64	138.29	0.040	0.18
0.5k_v3	500	56	4.67 / 12.40	50.09 - 69.70	*43.10 - 80.76*	P / D	0.99	33.05	9.27	90.14	0.036	0.16
0.5k_v4	500	56	16.25 / 11.05	39.29 - 87.65	38.90 - 83.11	P / P	1.98	13.82	16.30	44.01	0.025	0.12
0.5k_v5	500	56	1.36 / 1.62	48.58 - 54.24	50.51 - 57.25	D / D	1.51	18.70	11.10	47.65	0.009	0.23
0.5k_v6	500	56	2.84 / 2.87	46.98 - 58.10	45.52 - 55.89	D / P	1.70	14.93	15.11	30.57	0.011	0.25
0.5k_v7	500	56	1.56 / 2.11	49.11 - 56.89	47.58 - 55.79	D / P	1.57	21.51	16.93	44.50	0.012	0.28
0.5k_v8	500	56	1.72 / 1.32	48.75 - 56.11	47.71 - 55.24	D / D	1.99	10.64	16.55	27.12	0.010	0.26
1k_v1	1000	512	3.94 / 2.25	48.19 - 65.68	48.32 - 58.03	P / P	1.95	18.80	18.79	45.44	0.012	0.20
1k_v2	1000	512	5.01 / 2.38	48.77 - 67.50	53.68 - 63.94	P / D	2.09	21.59	16.94	57.74	0.016	0.21
1k_v3	1000	512	2.66 / 1.81	49.38 - 61.68	49.99 - 58.78	P / P	2.06	16.43	17.84	40.51	0.012	0.20
1k_v4	1000	512	2.04 / 1.51	46.69 - 57.45	50.58 - 57.89	P / D	1.43	17.97	13.60	34.97	0.015	0.24
1k_v5	1000	512	7.16 / 4.75	53.76 - 78.61	51.42 - 71.40	P / P	1.98	20.79	16.46	55.83	0.017	0.22
1k_v6	1000	64	3.63 / 3.15	42.00 - 56.92	47.92 - 60.18	P / D	1.35	15.27	14.57	38.42	0.016	0.30
1k_v6	1000	512					2.11	18.13	18.00	45.96	0.013	0.23
1k_v7	1000	64	3.63 / 2.91	51.82 - 67.31	48.45 - 61.55	P / P	1.48	25.97	12.03	51.89	0.020	0.28
1k_v7	1000	512					1.58	22.87	16.68	52.33	0.016	0.24
1k_v8	1000	64	7.87 / 2.37	54.49 - 85.44	47.97 - 57.84	P / P	1.43	26.76	13.26	56.68	0.023	0.28
1k_v8	1000	512					2.04	21.41	16.11	67.72	0.019	0.21
2k_v1	2000	512	5.64 / 4.02	50.05 - 71.68	52.80 - 71.20	P / D	1.74	16.61	19.44	36.87	0.013	0.23

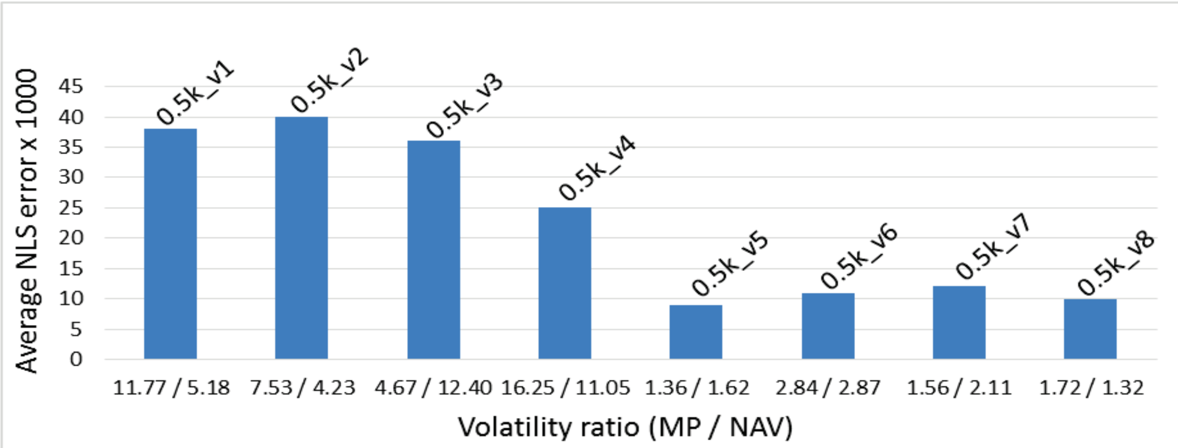

FIGURE 5. The average NLS error comparison for the time series having various volatility levels.

CONCLUSIONS

This paper complements the project report [10] about the development and assessment of the parallel nonlinear parameter optimization algorithm with classified IPV pools. In this work, we evaluated the convergence of the model parameter vector, the NLS error and MIF to quantify the success of the optimization process depending on the number of IPVs and financial market situations such as the presence of low volatility, high volatility and stock MP at a discount/premium to its NAV. We obtained smaller NLS errors and better MIF via the parallel algorithm compared to the serial algorithm with fixed initial parameter pool having less number of IPVs, based on the dataset. Moreover, we observe that generally the NLS error is larger for the time series pair as proxy to MP and NAV whose volatilities are sufficiently higher for both MP and NAV when the other variables are fixed. Finally, we consider different work scheduling and load balancing strategies. We try dynamic IPV assignments to cores. For example, first, each core can launch with one parameter vector and seek to take new one when it completes the task.

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