

Block Length Selection for Block Bootstrap in MATLAB and Octave using BLeS

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Software

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Summary

We present a MATLAB toolbox called BLeS (Block Length Selection) for selecting the block length, the primary tuning parameter in block bootstrap, a resampling method for estimating an empirical distribution of dependent data. This package enables users to select block lengths using various methods provided by different scholars for several well-known block bootstrap approaches. The implementations include the Hall-Horowitz-Jing (HHJ) method, the Bühlmann-Künsch (BK) method, the corrected Politis-White (cPW) method, the nonparametric plug-in (NPPI) method, block-length selections for the tapered block bootstrap (TBB) variants, and the Bertail-Dudek (BD) method. This toolbox has been tested using different examples from published articles, and a simulation study illustrating its range and functionality has been presented. BLeS is also supported in Octave.

Statement of Need

Bootstrapping is a resampling method used to approximate properties of an estimator, such as bias, variance, and its distribution. The standard bootstrap assumes independent and identically distributed (IID) data (Efron & Tibshirani, 1993), and therefore it is unsuitable for correlated observations (Künsch, 1989). To handle dependence, block bootstrap resamples blocks of consecutive observations from a correlated series instead of individual IID points (Hall et al., 1995). Block bootstrap has several variants—fixed, moving/overlapping, circular, stationary, etc.—but in all cases the key issue is choosing the block length (Lahiri, 1999), which largely determines its performance. Thus, block length is the primary tuning parameter, and its selection is a crucial research problem.

There exist several mean-squared error (MSE)-optimal block lengths in some cases; however, they cannot be obtained in practice due to the inclusion of population parameters. As a result, the available literature focuses on empirical block length choices for a certain block bootstrap variant. Pioneering articles include Hall et al. (1995), Bühlmann & Künsch (1999), Paparoditis & Politis (2002), Politis & White (2004), Lahiri et al. (2007), Shao (2010), Gregory et al. (2018), Bertail & Dudek (2024). For a detailed overview and comparison of their capabilities, we refer readers to Tabassum & De Brabanter (2026, In Review).

Because these methods have been developed for practical purposes, their implementation and ease of use are of prime importance. Although some free-source codes for block bootstrap can be found (see [here](#) for bboot in R, and [here](#) for some MATLAB codes), there are only a few sources that implement block length selection algorithms. We have identified some sources that, in some capacity, have implemented some of the methods available in the literature. The most frequently implemented ones are by Politis & White (2004) and Hall et al. (1995), while there are almost nonexistent sources for the other methods, to the best of our knowledge.

Therefore, there is a need for an extensive toolbox/package that offers implementations for the available and widely used block length selectors.

State of the Field

The available block length selectors are presented in Table 1.

Table 1: Overview of available software implementations related to block length selection.

Package / Function(s)	Author(s)	Capabilities	Environment	Source
opt_block_length_REV_dec07	Patton (2007)	Block length selector for CBB and SBB	MATLAB	Andrew Patton's Matlab Page
b.star	Hayfield & Racine (2008)	Block length selector for CBB and SBB	R	np package
getNPPIblksizeQR	Gregory (2022)	Block length selector MBB, SMBB, ETBB, and SETBB for quantile regression	R	QregBB package
optimal_block_length	Nowotny (2019)	Block length selector for CBB and SBB	Python	recombinator package
optimal_block_length	Sheppard (2021)	Block length selectors for CBB and SBB	Python	arch package
OBL	James & Kayode (2022)	Block length selector for NBB, MBB, CBB, TMBB, and TCBB	R	OBL package
blocklength	Stashevsky (2025)	Block length selector for HHJ, cPW, and NPPI	R	blocklength package
boodd	Bertail & Dudek (2025)	Block length selector for BD	R	boodd package

Notes: BB: Block bootstrap; CBB: Circular BB; SBB: Stationary BB; MBB: Moving BB; SMBB: Smooth MBB; ETBB: Extended tapered BB; SETBB: Smooth ETBB; HHJ: Hall–Horowitz–Jing; cPW: corrected Politis–White; NPPI: Nonparametric plug-in; NBB: Non-overlapping BB; TMBB: Tapered MBB; TCBB: Tapered CBB; TBB: Tapered BB.

To address the gap in the available implementations for block length selection, BLeS includes the implements for the HHJ method (Figure 1), BK method (Figure 2), cPW method (Figure 3), NPPI method (Figure 4), the block length selectors for the tapered block bootstrap variants (Figure 5, Figure 6), and the BD method (Figure 7).

Software Design

Given that resources for block length selection methods are not readily available in many cases, and those that are available are scattered, we propose the BLeS toolbox in MATLAB and Octave, which contains implementations of nearly all available block length selection methods in one place. The unique characteristics of this toolbox are that it: (1) provides a user-oriented implementation scheme for almost every block length selection method available in the literature, offering ease-of-use through only one line of code and the opportunity to customize the inputs, (2) presents the replication material corresponding to several published sources including Hall et al. (1995), Bühlmann & Künsch (1999), Politis & White (2004), Lahiri et al. (2007) and so on, and (3) contains both MATLAB and Octave implementations to provide more flexibility to the users. We have employed consistent notations from the block bootstrap literature and adhered to the conventions of the source articles to minimize any notational and argumentative discrepancies. Detailed instructions and documentation, along with examples, are created to ensure that users can navigate BLeS successfully.

Research Impact Statement

BLeS is the first MATLAB and Octave toolbox to provide convenient implementations for almost all the available block length selection methods in block bootstrap, to the best of our knowledge. In addition to the implementations, the BLeS repository contains the replication materials corresponding to the Simulations section of Tabassum & De Brabanter (2026, In Review), where different block length selectors have been evaluated against each other using benchmark examples. The contribution of BLeS to the research in the block bootstrap field is thus strengthened not only by the comprehensive availability of the available methods but also by the reproducible materials.

AI Usage Disclosure

- Tool use: ChatGPT-5 was used to speed up chunks of code, which were mentioned explicitly in comments in the source code.
- The nature and scope of assistance: Code speedup.
- Confirmation of review: We, the authors, assert that we have reviewed, edited, and validated all AI-assisted outputs and made the core design decisions.

References

- Bertail, P., & Dudek, A. (2024). Optimal choice of bootstrap block length for periodically correlated time series. *Bernoulli*, 30(3), 2521–2545.
- Bertail, P., & Dudek, A. (2025). *Bootstrap for dependent data, with an R package*. <https://cran.r-project.org/package=boodd>
- Bühlmann, P., & Künsch, H. (1999). Block length selection in the bootstrap for time series. *Computational Statistics & Data Analysis*, 31(3), 295–310.
- Efron, B., & Tibshirani, R. (1993). *An introduction to the bootstrap*. Chapman & Hall.
- Gregory, K. (2022). *QregBB: Block bootstrap methods for quantile regression in time series*. <https://cran.r-project.org/web/packages/QregBB>
- Gregory, K., Lahiri, S., & Nordman, D. (2018). A smooth block bootstrap for quantile regression with time series. *The Annals of Statistics*, 46(3), 1138–1166.

- 94 Hall, P., Horowitz, J., & Jing, B.-Y. (1995). On blocking rules for the bootstrap with dependent
95 data. *Biometrika*, 82(3), 561–574.
- 96 Hayfield, T., & Racine, J. (2008). Nonparametric econometrics: The np package. *Journal of*
97 *Statistical Software*, 27(5). <http://www.jstatsoft.org/v27/i05/>
- 98 James, D., & Kayode, A. (2022). *OBL: Optimum block length*. [https://cran.r-project.org/](https://cran.r-project.org/web/packages/OBL/vignettes/OBL.html)
99 [web/packages/OBL/vignettes/OBL.html](https://cran.r-project.org/web/packages/OBL/vignettes/OBL.html)
- 100 Künsch, H. (1989). The jackknife and the bootstrap for general stationary observations. *The*
101 *Annals of Statistics*, 1217–1241.
- 102 Lahiri, S. (1999). Theoretical comparisons of block bootstrap methods. *The Annals of*
103 *Statistics*, 386–404.
- 104 Lahiri, S., Furukawa, K., & Lee, Y.-D. (2007). A nonparametric plug-in rule for selecting
105 optimal block lengths for block bootstrap methods. *Statistical Methodology*, 4(3), 292–321.
- 106 Nowotny, M. (2019). *Recombinator - statistical resampling in python*. [https://github.com/](https://github.com/InvestmentSystems/recombinator)
107 [InvestmentSystems/recombinator](https://github.com/InvestmentSystems/recombinator)
- 108 Paparoditis, E., & Politis, D. (2002). The tapered block bootstrap for general statistics from
109 stationary sequences. *The Econometrics Journal*, 5(1), 131–148.
- 110 Patton, A. (2007). *Code for Politis and White's (2004) automatic block-length selection*
111 *procedure*. <https://public.econ.duke.edu/~ap172/code.html>
- 112 Politis, D., & White, H. (2004). Automatic block-length selection for the dependent bootstrap.
113 *Econometric Reviews*, 23(1), 53–70.
- 114 Shao, X. (2010). Extended tapered block bootstrap. *Statistica Sinica*, 807–821.
- 115 Sheppard, K. (2021). Bashtage/arch: Release 7.2 (version 7.2). *Zenodo*, 593254. <https://doi.org/10.5281/zenodo.15681>
- 116
- 117 Stashevsky, A. (2025). *Blocklength: Select an optimal block-length to bootstrap*
118 *dependent data (block bootstrap)*. <https://alecstashevsky.com/r/blocklength>,
119 <https://github.com/Alec-Stashevsky/blocklength>
- 120 Tabassum, M., & De Brabanter, K. (2026). A state-of-the-science overview of block length
121 selection methods in block bootstrap. *Statistical Science*.

122 Appendix

123 In this section, we present the graphical representations of the block length selectors in BLeS.
124 For details of these methods, the readers are referred to the source articles and Tabassum &
125 De Brabanter (2026, In Review) for a comprehensive overview.

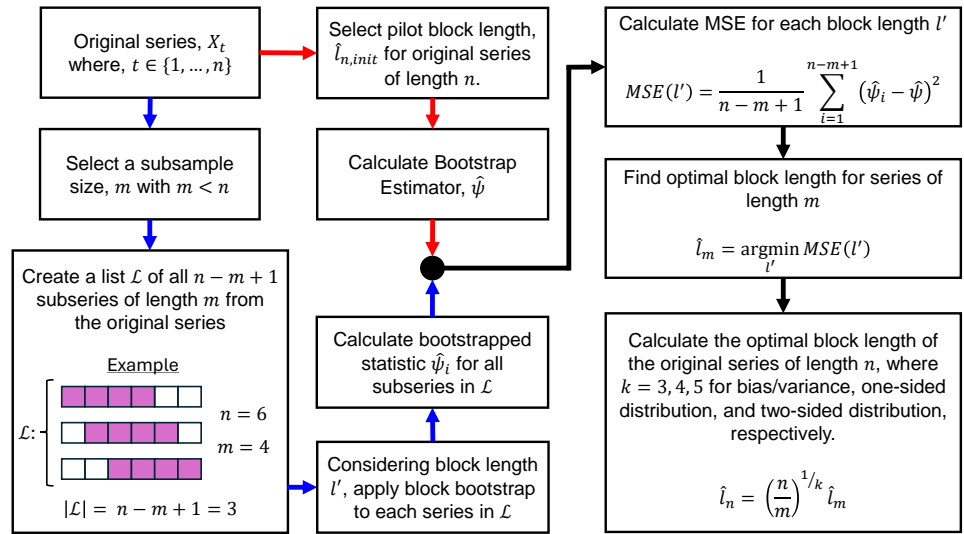


Figure 1: Hall-Horowitz-Jing (HHJ) method of block length selection.

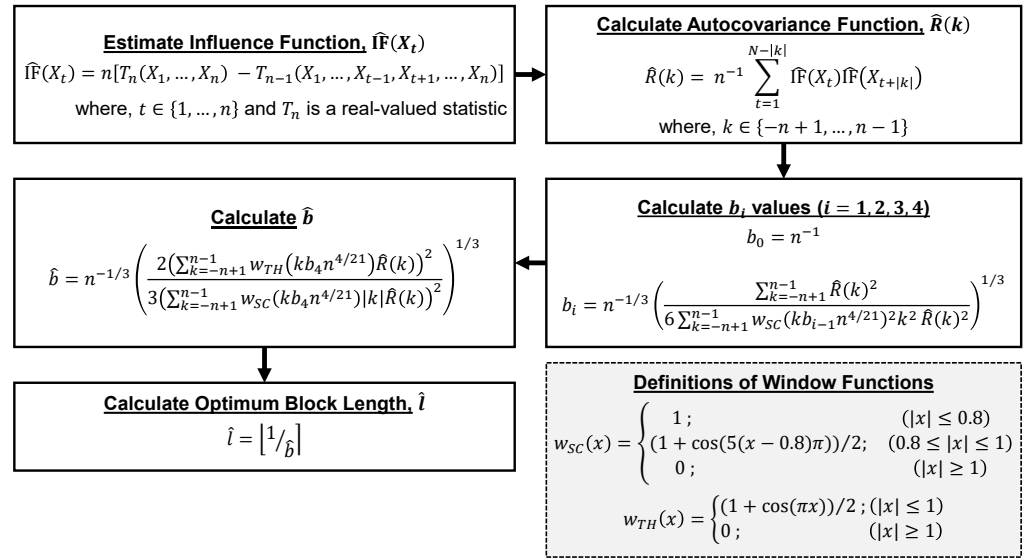


Figure 2: Bühlmann-Künsch (BK) method of block length selection.

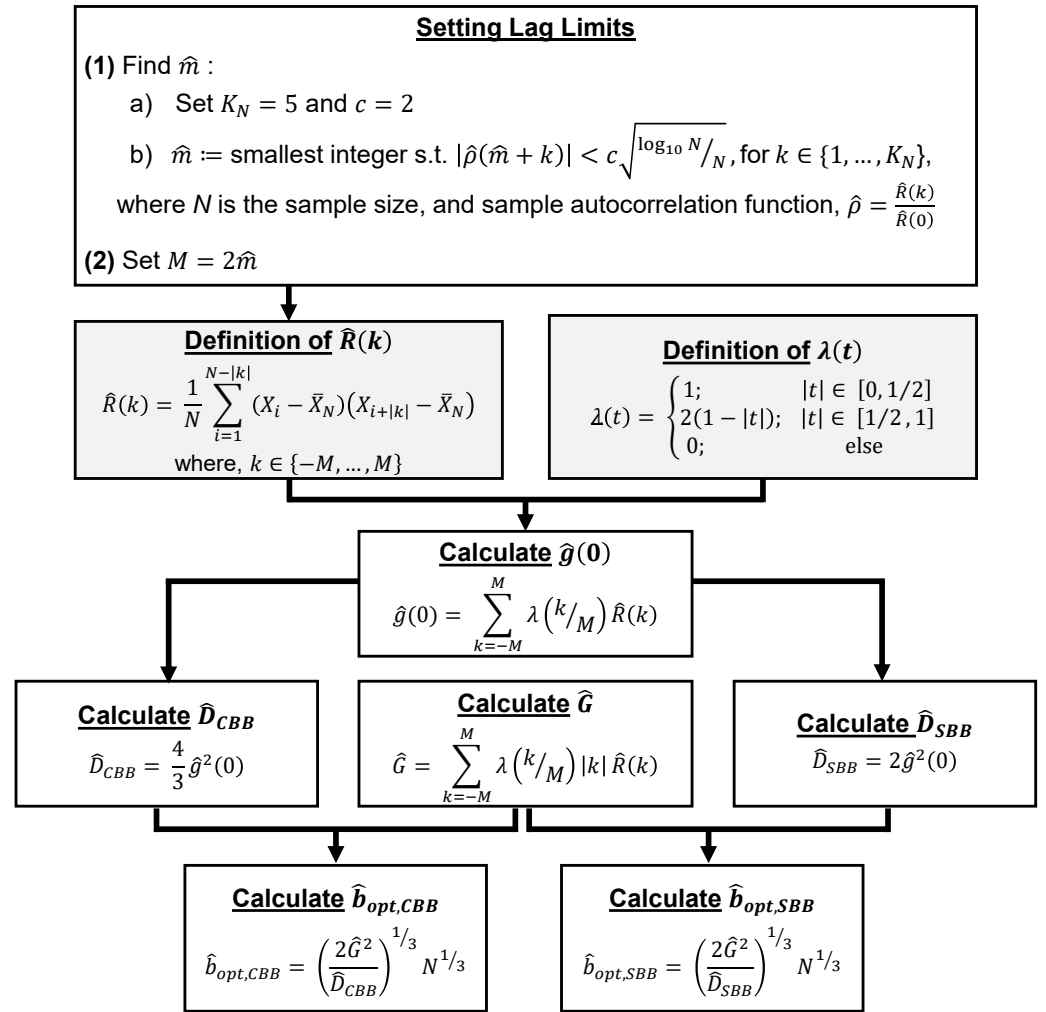


Figure 3: Corrected Politis-White (cPW) method of block length selection.

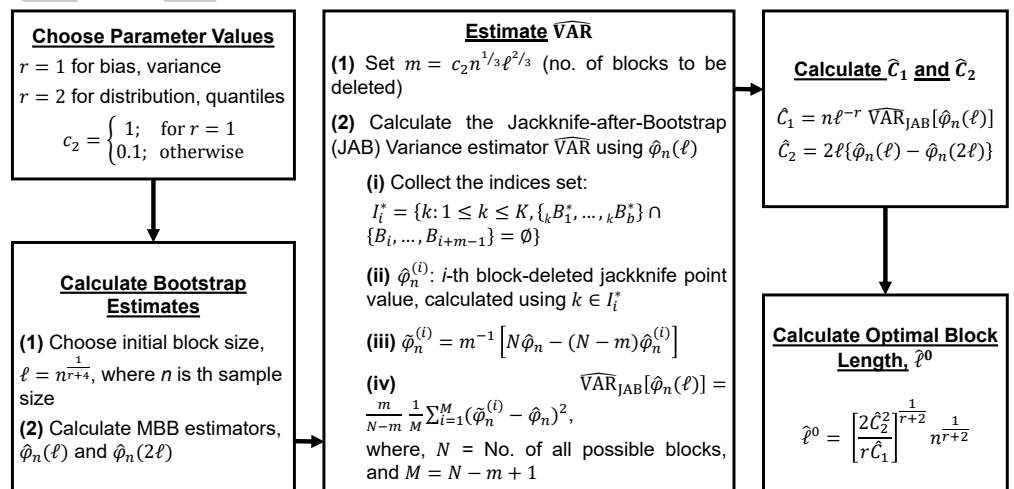


Figure 4: Nonparametric plug-in (NPPI) method of block length selection.

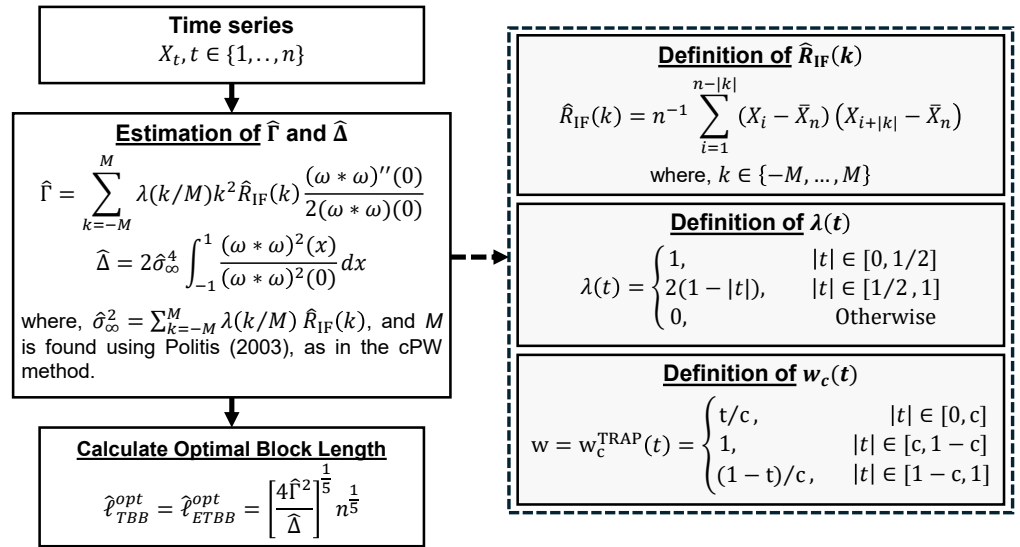


Figure 5: Block length selection for tapered block bootstrap (TBB), and its extended version (ETBB). (Politis, D. N. (2003). Adaptive bandwidth choice. *Journal of Nonparametric Statistics*, 15(4-5), 517-533.)

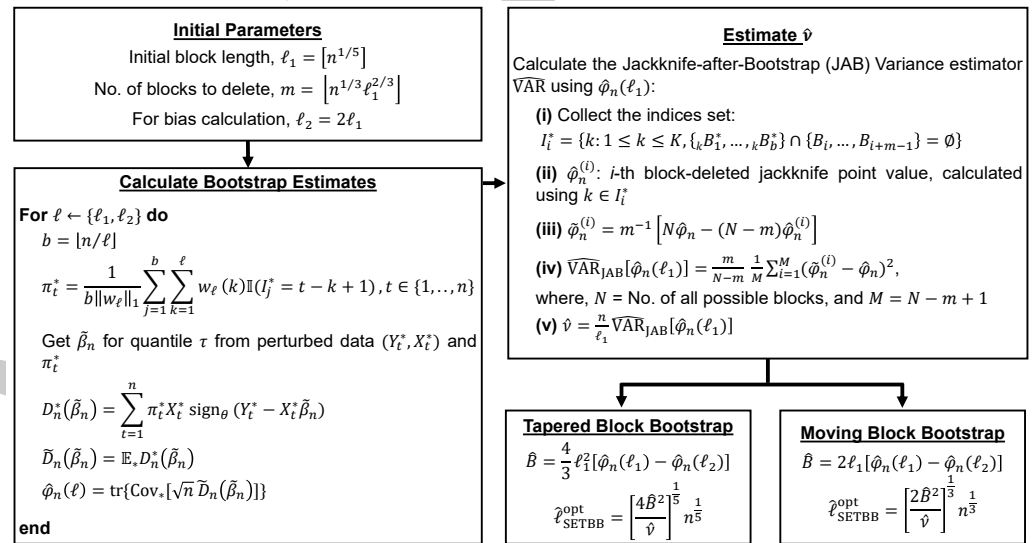


Figure 6: Block length selection for smooth extended tapered block bootstrap (SETBB).

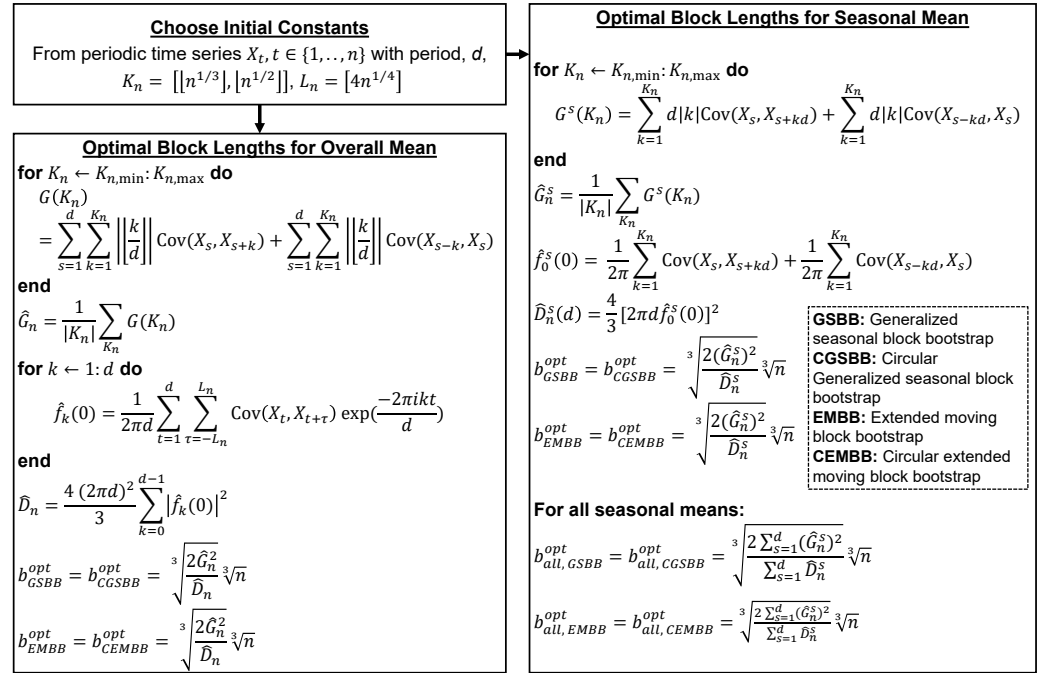


Figure 7: Block length selection using BD method.