



Nowcasting Quarterly Output Growth With Mixed-Frequency Electricity and Freight Indicators

Tigran Lefebvre^{1*}, Astrid Alvarez², Astrid Saleh³

¹Department of Business, Balkan Graduate Institute of Business, Bangladesh

²Department of Business, Bharathapuzha University Centre for Business, Kenya

³Department of Business, Pearl River Research Institute of Business, Guyana

Article Info

Volume 1, Issue 1, 2026

[doi: 10.62715/ijafe.2026.v1.i1.pp20-25](https://doi.org/10.62715/ijafe.2026.v1.i1.pp20-25)

Received: 22 May 2026

Accepted: 07 July 2026

Published: 14 September 2026

Abstract

Official estimates of quarterly output arrive weeks or months after the quarter ends, and in many economies the monthly indicators that forecasters elsewhere rely on are sparse, late or heavily revised. Electricity consumption and freight movements are attractive substitutes: they are recorded daily or weekly for operational reasons, are available within days, and are closely tied to production and trade. They also carry noise from weather, holidays and structural change that can mislead if ignored. This article proposes a procedure for building a nowcast of quarterly output growth from such indicators. The procedure has seven steps: assembling the series with their release calendar, cleaning and adjusting them for temperature, calendar and seasonal effects, aligning the frequencies, specifying an autoregressive benchmark together with bridge, mixed-data sampling and small factor models, evaluating all of them in a pseudo-real-time exercise that respects publication lags, comparing and combining the forecasts, and reporting the nowcast with a statement of its uncertainty. The reasoning behind each step is given, along with the choices that suit short samples and limited statistical capacity. The procedure draws on established econometric methods. It is a proposal and has not been applied to data or validated in this article.

Keywords: *Nowcasting, Mixed-frequency data, MIDAS regression, Electricity consumption, Freight indicators, Real-time forecasting*

© 2026 Tigran Lefebvre et al. This is an open access article under the CC BY license (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

1. Introduction

Policy makers must judge the present state of the economy before the national accounts describe it. Nowcasting is the name given to forecasting the current or the just-completed quarter using information that arrives earlier and more often than the target itself. The approach formalised by Giannone *et al.* (2008) treats the nowcast as something to be updated each time a new release appears, and the methods that have followed are surveyed by Bańbura *et al.* (2013). Most applications use a large panel of monthly surveys, production indices and labour market data.

Many statistical systems cannot supply such a panel. Business surveys may not exist, industrial

* Corresponding author: Tigran Lefebvre, Department of Business, Balkan Graduate Institute of Business, Bangladesh. E-mail: tigran.lefebvre@balkan.edu

© 2026 Tigran Lefebvre et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

production may be published with a long delay, and monthly labour data may cover only part of the workforce. What these economies do have are records generated by the operation of infrastructure. Grid operators log electricity load continuously. Railways, ports, toll roads and customs authorities count wagons, containers, vehicles and declarations as they pass. These series are timely, frequent and not subject to sampling error, and interest in them grew sharply when conventional statistics were disrupted in 2020 and weekly activity indices built from high-frequency data came into regular use (Lewis et al., 2022).

This article sets out a procedure for turning electricity and freight indicators into a nowcast of quarterly output growth. It is written for analysts in central banks, finance ministries and statistical offices who have a short history of quarterly accounts and a small team. The procedure is proposed on the basis of published methods. It is not applied to any country's data here, and no forecasting performance is claimed for it.

2. Electricity and Freight as Activity Indicators

Electricity is an input to almost all production and cannot be stored cheaply at scale, so consumption tracks activity closely in time. The relation is strongest for industry and weakest for households, whose demand is driven by temperature and by the calendar. The link between electricity and output also shifts slowly as the economy moves towards services, as equipment becomes more efficient, and as firms install their own generation, which removes load from the grid without any fall in production. Where supply is rationed, recorded consumption measures what the system could deliver and not what users wanted.

Freight indicators measure the movement of goods and therefore capture industry, construction, trade and agriculture more than services. Volume measures such as rail tonne-kilometres, port container throughput and heavy-vehicle toll counts relate directly to domestic activity. Freight rates are a different kind of series: they reflect the balance of demand and shipping capacity and have been used to proxy global demand, as in the index of real activity constructed by Kilian (2009). Customs declarations and electronic waybills, where the tax administration records them, extend the coverage to road haulage, which carries most domestic freight in many countries and is otherwise the least well measured mode. Volumes are affected by strikes, port congestion, weather and changes in the split between road and rail. Neither electricity nor freight says much about public administration or most private services, a limit on what any nowcast built from them can achieve.

3. Models for Mixed Frequencies

The econometric problem is to relate a quarterly target to indicators observed monthly, weekly or daily, some of which are only partly available for the current quarter. Three families of models address it. Bridge equations aggregate each indicator to quarterly frequency, after extending it over the missing part of the quarter with an auxiliary forecast, and regress output growth on the aggregates (Baffigi et al., 2004). Mixed-data sampling (MIDAS) regressions keep the indicator at its original frequency and impose a parsimonious weighting function on its lags (Ghysels et al., 2007); Clements and Galvão (2008) added an autoregressive term and applied the model to output growth. When the frequency gap is small, as between months and quarters, the weights can be left unrestricted and estimated by least squares (Feroni et al., 2015).

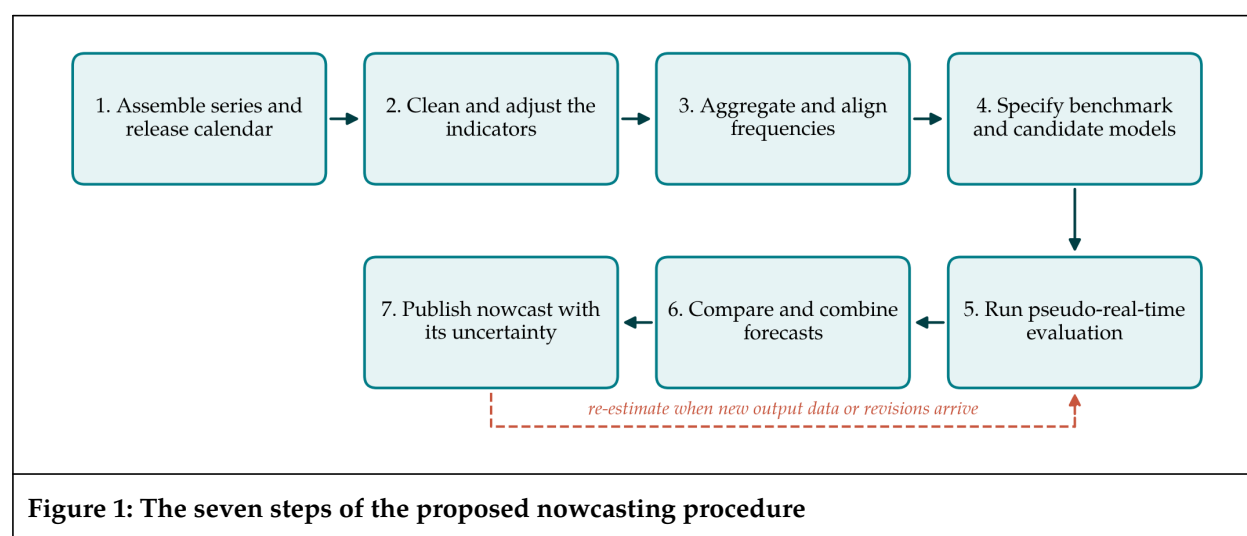
The third family casts the problem in state space. Mariano and Murasawa (2003) showed how quarterly output can be treated as a monthly series with missing observations and linked to a common factor, and Bańbura and Modugno (2014) gave an estimation method for factor models with arbitrary patterns of missing data that also decomposes each revision of the nowcast into the contributions of individual releases. Comparisons of MIDAS with mixed-frequency vector autoregressions suggest that the approaches are complements, with relative performance depending on the horizon (Kuzin et al., 2011). Table 1 summarises the candidates considered in the procedure and the circumstances that favour each.

Table 1: Candidate model classes for the nowcast, with their main strengths and limits in short samples

Model class	How frequencies are joined	Strength	Limit
Autoregressive benchmark	Quarterly data only	Simple yardstick for all others	Ignores within-quarter information
Bridge equation	Indicators forecast, then averaged to quarters	Transparent; easy to explain	Needs an auxiliary forecast for each indicator
MIDAS	Weighted high-frequency lags enter directly	Few parameters; handles weekly data	Nonlinear estimation; weights may be fragile
Unrestricted MIDAS	Each monthly lag has its own coefficient	Estimated by least squares	Parameter count grows quickly
Small dynamic factor model	State space with missing observations	Handles the ragged edge; news decomposition	More demanding to build and maintain
Forecast combination	Average of the models above	Robust to instability in any one model	Hides which indicator drives the result

4. The Proposed Procedure

The procedure has seven steps, shown in Figure 1. They are described in the order in which an analyst would carry them out, and the loop back to the start reflects the fact that a nowcasting system is re-estimated whenever a new quarter of output data, or a revision to earlier quarters, is published.



4.1. Step 1: Assemble the series and the release calendar

The analyst collects the quarterly output series, the electricity series and the freight series at the highest frequency available, and records for each the delay between the reference period and publication. For output, successive vintages should be kept wherever the statistical office has archived them, because the first estimate, which is what the nowcast will be judged against, can differ materially from the latest (Croushore and Stark, 2001). Electricity should be obtained separately for industrial and other users if the utility records it so. Each freight series should be documented with its coverage and any known breaks.

4.2. Step 2: Clean and adjust the indicators

Raw load and traffic data are dominated by patterns unrelated to the business cycle. The temperature effect on electricity is removed by regressing daily load on heating and cooling degree days and keeping the remainder. Weekends, public holidays and holidays that move with the lunar calendar are handled

with day-type indicators before any aggregation. Periods of supply rationing and major outages are flagged and treated as missing, not as low activity. Seasonal patterns that remain are removed with a method that tolerates gaps and changing seasonality, such as the loess-based decomposition of [Cleveland et al. \(1990\)](#). The adjusted series are then expressed as growth rates on the same basis as the output series.

4.3. Step 3: Aggregate and align frequencies

Daily data are averaged to weeks or months according to the model in which they will be used. With a decade or so of quarterly observations, monthly aggregation is usually the prudent choice, since it limits the number of high-frequency lags. The analyst then constructs, for each date on which a nowcast is to be produced, the data set as it would have looked on that date, with the trailing observations that had not yet been published left blank. This uneven end of the sample is known as the ragged edge, and reproducing it faithfully is what separates a nowcasting evaluation from a regression fitted with hindsight.

4.4. Step 4: Specify the benchmark and the candidate models

A first-order autoregression of quarterly growth, together with the historical mean, serves as the benchmark. Against it the analyst specifies one bridge equation per indicator, a MIDAS regression with an autoregressive term for each indicator, an unrestricted version where monthly data are used, and, if capacity allows, a small factor model containing all indicators. Models are kept small on purpose. With short samples a regression containing electricity and two freight series already uses a noticeable share of the available degrees of freedom, and the temptation to add every available transport series should be resisted.

4.5. Step 5: Run a pseudo-real-time evaluation

Each model is estimated on an initial window and used to nowcast the next quarter from the data set constructed in step 3; the window is then extended by one quarter and the exercise repeated. Nowcasts are produced at several points, for example at the end of each month of the quarter and one month after it ends, so that the gain from each additional month of indicator data can be seen. Errors are measured against the first official release. All choices of specification, including lag lengths and the adjustment regressions in step 2, are made using only the data in the estimation window at each point.

4.6. Step 6: Compare and combine the forecasts

Root mean squared and mean absolute errors are reported for each model and horizon relative to the benchmark. Differences are assessed with the test of [Diebold and Mariano \(1995\)](#), and with the adjusted statistic of [Clark and West \(2007\)](#) where the benchmark is nested in the larger model. With few evaluation quarters these tests have little power, and their results should be read as indicative. Because the best single model often changes from one period to the next, the procedure recommends that the published nowcast be a combination. A simple average is hard to beat in practice, a long-standing result since [Bates and Granger \(1969\)](#) that is discussed at length by [Timmermann \(2006\)](#).

4.7. Step 7: Publish the nowcast with its uncertainty

The nowcast is released as a point estimate with a range derived from the errors recorded in step 5 at the corresponding point in the quarter. The note that accompanies it should state which indicator releases moved the estimate since the previous round, and should identify any adjustment made by judgement. Where a factor model is used, the news decomposition of [Bańbura and Modugno \(2014\)](#) supplies this attribution directly.

5. Fitting the Procedure to Limited Capacity

A team of two or three analysts can run steps 1 to 6 with bridge and MIDAS models in open-source statistical software, and can add the factor model later. The larger demands are institutional. Grid and transport operators must agree to deliver data on a fixed schedule and to report changes in coverage, which is best secured by a written agreement. Where quarterly accounts are themselves compiled partly from electricity or freight data, as happens when direct measures of output are missing, the nowcast will

appear more accurate than it is, because indicator and target share an input. The analyst should ask the statistical office how the early estimates are built before interpreting any evaluation.

6. Limitations and What Remains to Be Shown

The procedure has not been tested in this article, and several of its premises are empirical. The relation between electricity and output may be too unstable in economies undergoing rapid electrification or frequent rationing for any fixed-coefficient model to work. Freight volumes may lag output where inventories are large. Short samples limit both estimation and evaluation, and a model that performs well over a few dozen quarters may owe that to a single episode. The indicators cover goods production and trade far better than services, so that errors will be largest when services and industry diverge. Whether a combination built from these indicators improves on the autoregressive benchmark, and at which point in the quarter, can only be established country by country through the evaluation described in step 5.

7. Conclusion

Electricity and freight records give economies with thin monthly statistics a workable basis for nowcasting, provided the indicators are cleaned with care and the evaluation respects what was known at each date. The seven steps proposed here favour small models, an explicit benchmark, forecast combination and plain reporting of uncertainty. They describe a method that has yet to be validated, and the test of it lies in application to real-time data.

Conflict of interest

To be declared by the author(s) before publication.

Funding

To be declared by the author(s) before publication.

References

- Baffigi, A., Golinelli, R. and Parigi, G. (2004). [Bridge models to forecast the euro area GDP](#). *International Journal of Forecasting*, 20(3): 447-460.
- Bates, J.M. and Granger, C.W.J. (1969). [The combination of forecasts](#). *Operational Research Quarterly*, 20(4): 451-468.
- Bañbura, M. and Modugno, M. (2014). [Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data](#). *Journal of Applied Econometrics*, 29(1): 133-160. <https://doi.org/10.1002/jae.2306>
- Bañbura, M., Giannone, D., Modugno, M. and Reichlin, L. (2013). [Now-casting and the real-time data flow](#). *Handbook of Economic Forecasting*, Vol. 2A: 195-237. Elsevier, Amsterdam.
- Clark, T.E. and West, K.D. (2007). [Approximately normal tests for equal predictive accuracy in nested models](#). *Journal of Econometrics*, 138(1): 291-311. <https://doi.org/10.1016/j.jeconom.2006.05.023>
- Clements, M.P. and Galvão, A.B. (2008). [Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the United States](#). *Journal of Business & Economic Statistics*, 26(4): 546-554.
- Cleveland, R.B., Cleveland, W.S., McRae, J.E. and Terpenning, I. (1990). [STL: A seasonal-trend decomposition procedure based on loess](#). *Journal of Official Statistics*, 6(1): 3-73.
- Croushore, D. and Stark, T. (2001). [A real-time data set for macroeconomists](#). *Journal of Econometrics*, 105(1): 111-130. [https://doi.org/10.1016/S0304-4076\(01\)00072-0](https://doi.org/10.1016/S0304-4076(01)00072-0)
- Diebold, F.X. and Mariano, R.S. (1995). [Comparing predictive accuracy](#). *Journal of Business & Economic Statistics*, 13(3): 253-263.
- Foroni, C., Marcellino, M. and Schumacher, C. (2015). [Unrestricted mixed data sampling \(MIDAS\): MIDAS regressions with unrestricted lag polynomials](#). *Journal of the Royal Statistical Society: Series A*,

178(1): 57-82.

Ghysels, E., Sinko, A. and Valkanov, R. (2007). [MIDAS regressions: Further results and new directions](#). *Econometric Reviews*, 26(1): 53-90.

Giannone, D., Reichlin, L. and Small, D. (2008). [Nowcasting: The real-time informational content of macroeconomic data](#). *Journal of Monetary Economics*, 55(4): 665-676.
<https://doi.org/10.1016/j.jmoneco.2008.05.010>

Kilian, L. (2009). [Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market](#). *American Economic Review*, 99(3): 1053-1069. <https://doi.org/10.1257/aer.99.3.1053>

Kuzin, V., Marcellino, M. and Schumacher, C. (2011). [MIDAS vs. mixed-frequency VAR: Nowcasting GDP in the euro area](#). *International Journal of Forecasting*, 27(2): 529-542.

Lewis, D.J., Mertens, K., Stock, J.H. and Trivedi, M. (2022). [Measuring real activity using a weekly economic index](#). *Journal of Applied Econometrics*, 37(4): 667-687.

Mariano, R.S. and Murasawa, Y. (2003). [A new coincident index of business cycles based on monthly and quarterly series](#). *Journal of Applied Econometrics*, 18(4): 427-443. <https://doi.org/10.1002/jae.695>

Timmermann, A. (2006). [Forecast combinations](#). *Handbook of Economic Forecasting*, Vol. 1: 135-196. Elsevier, Amsterdam.