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“MSc. in Supply Chain Management”

Master Dissertation

“ Forecasting Demand in poultry industry”

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Abstract

This thesis examines the Greek broiler sector of poultry industry and evaluates a range of time-series forecasting methods in order to identify the most accurate model for monthly demand prediction. The study begins with the analyses of the market environment of the sector, focusing on industry structure, channels of distribution, consumer demand patterns, state's regulatory constraints and the economic conditions by producers which have to face.

The methodological part compares several forecasting approaches, including moving averages, weighted moving averages, simple exponential smoothing, trend-adjusted smoothing, and regression-based models with trend and seasonality. The models are assessed primarily through Mean Absolute Deviation (MAD), so that the comparison is made based on the actual prediction of deviation in the same units of measurement in the series.

The findings shows that the linear trend model with seasonality provides the best overall performance, with the lowest MAD among the examined specifications and also superior accuracy compared with the smoothing-based alternatives. The results confirm that monthly broiler demand in the examined dataset is shaped by both a long-term upward trend and recurring seasonal fluctuations.

Overall, the thesis demonstrates that combining sectoral analysis with quantitative forecasting can support more informed managerial decisions in production planning, inventory control, and supply chain coordination. The proposed framework is especially relevant for perishable and sensitive food markets where small forecasting errors can have significant operational and financial consequences.

Keywords

Poultry industry, forecast models, weighted moving average, exponential smoothing, regression models, forecast

Περίληψη

Η παρούσα διπλωματική εργασία εξετάζει τον ελληνικό κλάδο broiler και αξιολογεί διάφορες μεθόδους πρόβλεψης χρόνο σειρών, με στόχο την επιλογή του πιο ακριβούς μοντέλου για μηνιαία πρόβλεψη ζήτησης. Αρχικά αναλύεται το περιβάλλον της αγοράς, με έμφαση στη δομή του κλάδου, τα κανάλια διανομής, τα πρότυπα ζήτησης των καταναλωτών, το ρυθμιστικό πλαίσιο και τις οικονομικές συνθήκες που έχουν να αντιμετωπίσουν οι παραγωγοί.

Το μεθοδολογικό μέρος συγκρίνει διάφορες προσεγγίσεις πρόβλεψης ,συμπεριλαμβανομένων των κινητών μέσων όρων, των σταθμισμένων κινητών μέσων όρων, της απλής εκθετικής εξομάλυνσης, της εξομάλυνσης προσαρμοσμένης τάσης και των παλινδρομικών μοντέλων με τάση και εποχικότητα. Τα μοντέλα αξιολογούνται κυρίως μέσω της Μέσης Απόλυτης Απόκλισης (MAD), ώστε η σύγκριση να γίνεται με βάση την πραγματική απόκλιση πρόβλεψης στις ίδιες μονάδες μέτρησης της σειράς.

Τα αποτελέσματα δείχνουν ότι το μοντέλο γραμμικής τάσης με εποχικότητα παρουσιάζει τη βέλτιστη συνολική επίδοση, με τη χαμηλότερη τιμή MAD μεταξύ των εξεταζόμενων υποδειγμάτων και καλύτερη ακρίβεια από τις εναλλακτικές μεθόδους

εξομάλυνσης. Τα αποτελέσματα αυτά επιβεβαιώνουν ότι η μηνιαία ζήτηση κοτόπουλων κρεατοπαραγωγής στο υπό εξέταση δείγμα επηρεάζεται τόσο από μακροχρόνια ανοδική τάση όσο και από επαναλαμβανόμενες εποχικές διακυμάνσεις.

Συνολικά, η εργασία καταδεικνύει ότι ο συνδυασμός τομεακής ανάλυσης με ποσοτική πρόβλεψη μπορεί να υποστηρίξει πιο τεκμηριωμένες διοικητικές αποφάσεις στον προγραμματισμό παραγωγής, στη διαχείριση αποθεμάτων και στον συντονισμό της εφοδιαστικής αλυσίδας. Το προτεινόμενο πλαίσιο είναι ιδιαίτερα σημαντικό για ευπαθείς και ευαίσθητες αγορές τροφίμων, όπου μικρά σφάλματα πρόβλεψης μπορούν να έχουν σημαντικές λειτουργικές και οικονομικές συνέπειες.

Λέξεις κλειδιά

Πτηνοτροφία , μοντέλα πρόβλεψης, κινητός μέσος όρος, εκθετική εξομάλυνση, μοντέλα παλινδρόμησης , πρόβλεψη.

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Introduction

Demand forecasting is a critical managerial function in modern supply chain systems, especially in sectors where products are perishable, Profit margins are narrow, and market conditions change rapidly. In the agri-food sector, and particularly in the Greek broiler industry, forecasting accuracy is directly linked to production planning, inventory control, distribution efficiency, and cost management. The structure of the thesis itself reflects this practical need: it moves from an analysis of the Greek broiler market environment to a comparative evaluation of forecasting models and finally to the identification of the most appropriate specification for operational and strategic decision-making.

The study begins by examining the broader market environment of the Greek broiler sector. Particular attention is given to market size and growth dynamics, the industry's vertically integrated structure, the role of contract farming, demand patterns, distribution channels, and the economic and regulatory pressures faced by firms and producers. This contextual discussion is not presented as background alone; rather, it establishes the conditions under which forecasting becomes indispensable. In a sector shaped by buyer concentration, seasonality, traceability requirements, cost volatility, and strong competitive pressure, the ability to estimate future demand with reasonable precision becomes a decisive factor for business performance.

Building on this sectoral analysis, the thesis then turns to the methodological core of the research. A set of forecasting techniques is presented and compared, including the simple moving average, weighted moving average, simple exponential smoothing, exponential smoothing with trend adjustment, linear trend regression, linear trend regression with seasonality, and the log-linear model with seasonality. The methodological discussion explains the theoretical basis of each approach and evaluates their relative strengths and limitations in relation to time-series demand data. In this way, the thesis creates a smooth transition from the qualitative characteristics of the broiler market to the quantitative tools required to model its demand behavior.

The empirical part of the study applies these techniques to monthly sales data and evaluates their performance mainly through the Mean Absolute Deviation (MAD), so that the comparison is grounded in practical forecast accuracy rather than in statistical fit alone. The results show that the linear trend model with seasonality outperforms the alternative specifications, indicating that the demand series is driven not only by a long-term trend but also by stable and recurring monthly fluctuations. This finding is especially important for a product category such as broiler meat, where inaccurate forecasts may lead either to stock shortages or too costly overstocking of highly perishable goods.

Taken together, the structure of the thesis follows a clear analytical logic.

Chapter 1 maps the economic and commercial environment of the Greek broiler sector,

Chapter 2 presents the forecasting framework and the theoretical foundations of the selected methods,

Chapter 3 applies these methods to real-world data and compares their results.

Through this progression, the thesis demonstrates that forecasting is not an isolated technical exercise, but an applied managerial tool embedded in the realities of a specific food supply chain.

Chapter 1: Market Environment of the Greek Broiler Sector

1.1 Market Size and Growth Dynamics

In the wider livestock and meat sector in Greece, the poultry sector has quietly emerged as one of the most dynamic sectors. It may not always make headlines like beef or dairy, but a closer look at the numbers tells a compelling story. Recent industry reports place the value of the Greek poultry market at around US$1.6-1.7 billion in 2024, with projections pointing to US$1.9 billion by 2033, with an expected annual growth rate of around 3-4% in value terms (ProMarketReports, 2025). These figures are broadly consistent with previous analyses of the Greek business press and the sectors that place the turnover of the broiler meat market at just over €1,5 billion. and identify a positive medium-term growth trajectory.

In terms of volume, international datasets of the market suggests that the total consumption of poultry meat in Greece reached around 297 thousand tons in 2023, based on several years of steady growth (ReportLinker, 2024a). What stands out here is the per capita rate: the average poultry meat consumption amounted to around 25.2 kg in 2023, with a moderate upward trend over the past five years and a compound annual growth rate of around 1.1% (ReportLinker, 2024b). This may sound modest, but it signals two things: resilience in demand and a gradual dietary shift in favor of poultry. In monetary terms, expenditure on fresh poultry meat amounted to around €94,07 per capita in 2023, following consecutive annual increases since 2021 (ReportLinker, 2024c).

From the perspective of self-sufficiency, Greece is in an interesting position. The country is relatively weak in terms of red meat, beef and pork, but has significantly better performance in poultry. ICAP CRIF Sector Notes (2025) state that poultry meat accounts for the largest share of total domestic meat production, with self-sufficiency remaining low in beef and pork but significantly higher in poultry. The data of the Broiler Innovation Network for Greece indicate that the country's self-sufficiency in broiler meat is in the range of 80-82%, with domestic integrators covering most of the internal demand and imports acting mainly as a complementary source or for specialized products (BIN Greece, 2023).

Taken all together, the quantitative data show a fairly clear picture: the Greek broiler sector combines a significant market size, relatively high self-sufficiency and a positive, allthough not explosive, growth trajectory. This positions it as a key pillar within the national meat supply system, and as we shall see in the sections that follow, it also creates a distinctive set of challenges and opportunities for the companies operating within it.

1.2 Industry Structure and Vertical Integration

One of the first things that strikes an observer of the Greek broiler industry is how concentrated it really is. A handful of large companies, vertically integrated from hatchery to supermarket shelf , dominate the landscape. Business and trade press frequently identify a core group of leaders, notably Pindos, Nitsiakos, Ambrosiadis, and Aggelakis, which together command the bulk of the organised broiler market, especially in branded and packaged poultry products. (Business Daily, 2021; IndustryARC, 2024a; Nitsiakos S.A., n.d.; PINDOS APSI, n.d.).

These companies typically operate under a fully integrated model, controlling most stages of the value chain: parent stock and hatcheries, feed manufacturing, veterinary services, slaughterhouses, cutting and deboning plants, further-processing facilities (e.g., marinated, breaded, and cooked products), packaging, and logistics. BIN Greece (2023) notes that six main broiler integrators provide their contracted farmers with virtually all required inputs day-old chicks, feed, veterinary supervision, technical advice, and sometimes energy or equipment, which illustrates the classic integrator–contract grower model in full operation.

It is worth noting that contract farming is really the defining feature of how the Greek broiler supply chain works in practice. Independent farmers invest in housing, labour, and day-to-day management, while the integrator retains ownership of birds and feed and assumes commercial responsibility for marketing the final product. In practice, this arrangement reduces price and market risk for growers, but also limits their autonomy and bargaining power, since they are effectively tied to a single buyer. From the integrator's perspective, contract farming allows flexible capacity expansion, risk sharing, and tighter control over biosecurity and production uniformity (see also comparable models in other EU countries; e.g., Kagkou, 2008).

Alongside the large integrators, a multitude of small and medium-sized poultry farms operate either as independent producers, supplying local butchers, open markets, and small chains or as contract growers attached to one of the major companies. Some of these smaller enterprises attempt to differentiate themselves through specialized placement, such as free-range or organic broilers, local labels, and "farm-to-table" concepts, though their aggregate market share remains modest relative to the integrated groups.

This structural configuration, few powerful integrators, many dependent growers, and a limited number of independent niche players, carries significant implications for price formation, risk allocation, innovation capacity, and the governance of the broiler supply chain in Greece. As we move through the rest of this chapter, these dynamics will resurface repeatedly.

1.3 Demand Patterns and Consumer Trends

Consumer demand has been central to the expansion of the broiler sector and understanding how it has evolved helps explain many of the industry's current dynamics. International and national evidence points to a long-term substitution of red meat by poultry, driven both by relative price considerations and by perceptions of poultry as a healthier protein source with lower saturated fat and a favorable nutrient profile (Tsitsos, 2021; MarketGrowthReports, 2025).

In Greece specifically, the increase in poultry consumption has been shaped by several intertwined trends:

1. **Price Sensitivity and "Value for Money."** The prolonged economic crisis, followed by the COVID-19 pandemic and more recent inflationary shocks in food and energy prices, have made Greek households acutely sensitive to food costs. Under these conditions, poultry offers a relatively affordable source of animal protein, making it a "core basket" product for many families. What is particularly telling , is that per-capita expenditure on poultry meat has risen in recent years despite stagnant or only slightly rising incomes, a clear illustration of its value-for-money positioning (ReportLinker, 2024c).
2. **Shift Towards Convenience and Ready-to-Cook Products.** The change of lifestyles, the increase in women's labor force participation and increasing time constraints have

expanded demand for convenience products such as marinated fillets, breaded portions, shawarma/gyros, skewers, and high-protein ready meals. Greek processors have responded by investing heavily in further-processed and ready-to-heat or ready-to-cook broiler products, often positioned as healthier alternatives to processed red meat(Grunert, 2006; IndustryARC, 2024b; Nitsiakos S.A., n.d.; Stamatopoulou & Tzimitra-Kalogianni, 2022). To put this into perspective, the variety of poultry-based convenience items available on supermarket shelves today would have been hard to imagine just a decade ago.

3. **Health, Quality, and "Clean Label" Concerns.** Consumers are more and more checking ingredient lists and production methods. Claims such as "no antibiotics as growth promoters," "non-GM feed," "animal welfare-friendly housing," and "slow-growing breeds" are gaining traction in European markets and are gradually being adopted in Greece as well (IndustryARC, 2024; MarketGrowthReports, 2025). This trend encourages differentiation strategies and supports premium segments, though price remains a powerful constraint for a sizeable portion of Greek consumers, a tension that producers have to consider carefully.
4. **Origin and Traceability.** Greek consumers attach significant value to national origin and traceability, especially after repeated episodes of "falsified origin" or so-called "Hellenizations" (mislabeling imported meat as domestic). The industry's response is enhanced labelling, national quality systems and digital traceability initiatives aimed at both restoring trust and protecting the competitive position of domestic producers (ICAP CRIF, 2025; BIN Greece, 2023).

In aggregate, these trends are pushing the Greek broiler market away from simple commodity whole carcasses and towards a portfolio of differentiated, value-added products that must still remain price competitive. It is a delicate balancing act, and one that shapes the commercial strategies explored later in this chapter.

1.4 Distribution Channels and Commercial Landscape

The structure of the channels of the Greek broiler market is more complex than it initially seems. Three main pillars underpin the distribution system, each with its own logical and commercial dynamics:

1. **Organised Retail (Supermarkets and Hypermarkets).** The organized retail sector absorbs most branded and packaged broiler sales (Pindos Agricultural Poultry Cooperative, n.d.). Large supermarket chains engage in annual framework agreements with integrators, negotiating prices, promotional budgets, volume commitments, and shelf space. A closer look reveals that private labels have grown significantly in importance; many chains now sell private-label poultry lines that are produced in the same plants as the integrators' own brands, intensifying intra-firm brand competition right at the shelf (Pindos Agricultural Poultry Cooperative, n.d.).

2. **Traditional Butcher Shops and Small Local Retailers.** Despite the expansion of supermarkets, the traditional butcher shop remains a central channel, especially in

smaller towns and rural areas. Industry studies and articles highlight that a significant share of meat markets in Greece still go through butchers, which have evolved into modern service-oriented stores that offer personalized cuts, prepared products and personalized advice (Provil S.A., n.d.a; Provil S.A., 2021). Especially for broiler meat, butchers often work with either local farmers or large integrators, using broilers as both a circulation driver and a margin generator, in particular through marinated, stuffed or ready-to-cook preparations (Papadopoulos Meat Company, 2025)

3. **HoReCa and Foodservice (Hotels, Restaurants, Catering).** The HoReCa channel represents a large and strategically important outlet for broiler products. Hotels, restaurants, fast-food outlets, rotisseries, and industrial kitchens demand stable volumes of standardized products such as breast fillets, strips, wings, burgers, gyros where often delivered in frozen or chilled form and in bulk packaging(Provil S.A., n.d.b; Sarikas-Kalenterian A.B.E.E., 2024). Given the seasonality of Greek tourism, the HoReCa channel exhibits strong seasonal peaks, which require close coordination between production planning, logistics, and sales forecasts (BIN Greece, 2023).

The coexistence of these channels built a multi-layered commercial environment that is anything but simple. Large integrators must simultaneously balance brand-building in supermarkets, serving demanding HoReCa customers, and maintaining partnerships with butchers, while smaller producers often rely on local networks and relational contracts with independent retailers. This heterogeneity in channels also shapes the design of outbound logistics, including delivery frequency, cold-chain requirements, and packaging formats that carry real implications for cost and risk management.

1.5 Economic and Production Environment for Farmers

The cost and income environment that Greek broiler farmers face is, to put it plainly, challenging(ICAP CRIF, 2025). Anyone familiar with agricultural economics will not be surprised to hear that margins are thin, but the specifics of the broiler sector make the situation especially demanding. The production cost structure is dominated by:

- **Feed costs** (maize, soybean meal, and other ingredients), which typically represent 60–70% of total variable costs (Feed Cost vs. Feed Quality, 2025) The Greek sector is highly exposed to global commodity price volatility and currency fluctuations, since a large share of feed ingredients is imported (ICAP CRIF, 2025).

- **Energy costs,** including electricity for ventilation, lighting, heating, and cooling systems, as well as fuel for transport. These have risen substantially in recent years due to global energy market instability, a reality that no Greek farmer can escape. (Tsouvaltzidis et al., n.d.).

- **Labor and compliance costs,** stemming from animal welfare regulations, environmental requirements (manure management, waste-water treatment), and biosecurity protocols (Broiler Innovation Networks, n.d.).

Under contract farming schemes, growers are typically paid per kilogram of live weight produced, adjusted for performance indicators such as feed conversion ratio (FCR) and mortality (Broiler Innovation Networks, n.d.).. However, numerous reports and stakeholders highlight that growers' profit margins are thin, with many complaining about insufficient compensation relative to their investment and risk exposure(Broiler Innovation Networks, 2023). BIN Greece (2023) notes that while integrators provide technical and input support, smaller contract farms often lack innovation capacity and bargaining power, making it difficult for them to upgrade technology or diversify their activities.

For independent farmers operating outside formal integration programs, the economic conditions are even more demanding. They must simultaneously manage production risk, market risk, and financial risk, including exposure to price fluctuations, late payments by buyers, and the absence of guaranteed absorption contracts (Kalogianni, 2024). In this context, risk management, either through the diversification of activities (e.g. on-farm processing, direct marketing, agrotourism), or through long-term supply agreements, or through participation in producer organizations, becomes critical for long-term sustainability (Kalogianni, 2014). As we'll see in later chapters, these farm-level pressures ripple outward and shape the entire supply chain.

1.6 Regulatory and Institutional Framework

No discussion of the Greek broiler sector would be complete without addressing the regulatory environment, which is both dense and consequential. The sector operates within a layered European and national regulatory framework, and the rules touch nearly every aspect of the business (European Commission, n.d.a). At the EU level, broiler production is governed by legislation in several key areas(European Commission, n.d.a):

- **Animal welfare,** including maximum stocking densities, lighting requirements, waste quality standards, and monitoring of health parameters (European Commission, n.d.a).

- **Food safety and hygiene,** covering slaughterhouse operations, Hazard Analysis and Critical Control Points (HACCP) systems, microbiological criteria, and residue limits for veterinary medicines (Better Chicken Commitment, n.d.).
- **Environment,** especially the Industrial Emissions Directive and related rules on ammonia emissions, waste management, and groundwater protection (European Commission, n.d.b).

At the national level, Greece has developed complementary rules and licensing procedures for poultry holdings and slaughterhouses, as well as specific provisions for small on-farm slaughter unit (Ministry of Rural Development and Food, 2024). s. These allow limited direct marketing of fresh poultry from the farm, but under strict conditions regarding annual slaughter volumes and distribution radius, a framework designed to protect both consumers and the integrity of the supply chain (eugo.gov.gr, 2024).

In response to recurrent concerns over mislabeling and the "Helenization" of imported meat, authorities have strengthened traceability and origin labelling, introducing stricter inspection regimes and distinctive markings for Greek-origin carcasses (Chatziargyri et al., 2022). National quality systems and the supervision of organizations such as ELGO–DIMITRA complement EU frameworks by promoting certified quality labels and enforcing compliance at retail and HoReCa levels(ICAP CRIF, 2025; Hellenic Agricultural Organization - DIMITRA, n.d.).

From a strategic viewpoint, this regulatory environment cuts both ways. it exerts cost pressure through compliance investments and on the other hand it underpins consumer trust in safety, quality, and origin. It also narrows the scope for low-cost, low-standards competition, thereby offering a degree of protection to firms that invest in high-quality production systems.

For the purposes of our analysis, this regulatory backdrop forms an important part of the risk landscape that broiler companies must navigate.

1.7 Specificities of Sales and Commercial Practices

The sales function in the Greek broiler sector is far from a simple matter of selling chicken. It exhibits several distinctive characteristics, closely linked to the product's perishability, the structure of the retail market, and the dual role of broilers as both commodity and differentiated product. In our analysis,seven features stand out: perishability and short shelf-life, retailer bargaining power, demand seasonality, promotion intensity, product differentiation, channel fragmentation and the need for accurate demand planning (Chopra & Meindl, 2019; Mentzer et al., 2001; Stamatopoulou & Tzimitra-Kalogianni, 2022).

1. **High Buyer Concentration and Strong Retailer Power.** A large share of broiler volumes flows through a small number of supermarket chains and major HoReCa distributors. This structure enhances the bargaining power of buyers, who can demand favorable pricing, extended credit terms, listing fees, and participation in promotional campaigns. Sector studies and trade press show that producers must allocate substantial budgets to trade promotions, including temporary price reductions, in-store displays, and advertising in leaflets. All of which significantly affect net margins (ICAP CRIF, 2022, 2025).

2. **Framework Agreements and Complex Commercial Terms.** Sales usually are ruled by annual or multi-year framework agreements rather than spot transactions. These

agreements determine not only base prices but also rappels (volume-based rebates), promotion offers, bonuses for category growth, service-level targets, and penalties for non-compliance. What this means in practice is that the real margin per kilogram depends on the overall management of the contract rather than solely on the nominal price (ICAP CRIF, 2025).

3. **Perishability and the Need for Rapid Stock Turnover.** Fresh broiler meat is highly perishable, with a short shelf life. Sales teams must coordinate closely with demand planning and logistics to ensure high rotation and to minimize returns, markdowns, and waste. This reality drives to the frequent use of promotions, offers and multi-packs to accelerate performance when demand drops, and it elevates the importance of accurate forecasting and flexible distribution (Broiler Net, 2024; Eurostat, 2024).

4. **Dual Strategy: Branded vs. Private Label Products.** Most major integrators simultaneously market their own brands and produce private-label products for retailers. This dual strategy creates internal trade-offs that are not always easy to manage: branded products support differentiation and premium positioning, while private-label contracts offer volume and capacity utilization but with tighter margins and potential cannibalization. The sales strategy must therefore carefully manage price architecture, packaging differentiation, and promotional calendars to avoid eroding the perceived value of branded lines (Market Research Future, 2025).

5. **Importance of B2B and HoReCa Sales and Technical Support.** In the HoReCa segment, sellers compete not only on price but also on service packages: product customization (specific cuts, portion sizes), stable supply, menu development support, and cost-per-portion optimization. Sales teams often act as technical advisors, helping

chefs standardize recipes and manage yield. This “consultative selling” approach is especially relevant for high-volume clients such as hotel chains, fast-casual restaurant chains, and industrial caterers.

6. **Role of Traditional Butchers in Value-Added Preparations.** For traditional butchers, broiler meat serves as a basic raw material for ready-to-cook preparations, marinated skewers, stuffed roasts, breaded fillets, which add value and differentiate the shop’s offering from the supermarket. Suppliers, whether integrators or spice and marinade companies, often provide recipe concepts, point-of-sale material, and training, thus transforming the sales relationship into a partnership focused on category development (Provil, 2021).

7. **Thin Margins and Limited Room for Pricing Errors.** Because broiler meat is simultaneously a basic and a quasi-commodity, gross margins per kilogram are relatively low while volumes are high. A small miscalculation in discounts, promotional budgets, or logistics costs can wipe out a significant portion of annual profit. This prioritizes accurate cost accounting, performance management, and the tight integration of commercial and financial planning, adding a layer of complexity to the sales function that should not be underestimated (Hellenic Competition Commission, 2021; ICAP CRIF, 2023; Eurostat, 2024).

Putting all together, the sales environment in the Greek broiler sector is highly structured, promotion-intensive, and operationally demanding. Companies need to synchronize pricing, promotions, logistics, and production to capture slim profit margins while managing significant volume and risk. It is, in many ways, a business where operational excellence is not a luxury but a survival requirement.

1.8 Synthesis and Implications

Having surveyed the various dimensions of the Greek broiler market environment, it is useful to consider what it all adds up to. We can observe that:

- The Greek broiler sector combines structural concentration, vertically integrated production, evolving consumer expectations, exposure to feed costs, energy and regulatory compliance. These elements make forecasting, channel allocation and risk-adjusted planning central to managerial decision-making (Chopra & Meindl, 2019; Hellenic Statistical Authority, 2025; Eurostat, 2025; IndustryARC, 2024a).
- The significant market size and the poultry meat production growth, although domestic production has never been sufficient to cover all Greek consumption, which in turn caused the continuous exposure to imports and trade conditions (Hellenic Statistical Authority, 2025; IndustryARC, 2024a; Stamatopoulou & Tzimitra-Kalogianni, 2022).
- A highly concentrated and vertically integrated industry structure, dominated by a few large integrators and supported by contract growers and specialized supply-chain arrangements (Business Daily, 2021; IndustryARC, 2024a; PINDOS APSI, n.d.).
- The evolving of consumer preferences towards affordable, convenient, health-oriented and traceable products, with food safety, quality cues and convenience playing an increasingly important role in poultry purchasing behaviour (Grunert, 2006; Stamatopoulou & Tzimitra-Kalogianni, 2022).
- A multi-channel commercial system, where organised retail, traditional butchers and HoReCa each play a distinct role in product positioning, service level requirements and demand variability (Chopra & Meindl, 2019; Mentzer et al., 2001).

- A cost-intensive production environment for farmers, dependent on volatile feed and energy prices and constrained by regulatory, animal-health and food-safety requirements (European Commission, 2017; Hafez & Attia, 2020).
- A complex, promotion-driven sales function characterised by strong retailer power, thin margins and the need for accurate planning, forecasting and risk management (Chopra & Meindl, 2019; Hyndman & Athanasopoulos, 2021; Makridakis et al., 1998).

Chapter 2: Research Methodology

Having identified the structural complexities, market volatility, and operational challenges that exist in the Greek broiler sector, it becomes clear that informed decision-making relies strongly on the ability to anticipate future demand. This chapter transitions from qualitive market description to quantitative analysis, presenting a forecasting framework that will transform market trends into actionable insights for supply chain optimization.

2.1 Introduction to the Forecasting Framework

Forecasting is the formal process of predicting future events based on historical data and mathematical modeling. In the context of Supply Chain Management (SCM), accurate forecasting is the primary driver for inventory control, production scheduling, and financial planning (Hyndman & Athanasopoulos, 2018). This study employs quantitative research design, focusing on time-series analysis to determine the most robust model for predicting demand.

The selection of a forecasting model is a trade-off between simplicity and sophistication. As noted by Heizer et al. (2020), a model must be complex enough to capture the underlying patterns of the data (trend, seasonality, and cycles) but simple enough to be computationally efficient and interpretable for management. This chapter details seven distinct methodologies, ranging from elementary smoothing techniques to advanced econometric regression models.

2.2 Simple Moving Average (SMA)

The Simple Moving Average (SMA) is one of the most fundamental techniques used in time-series forecasting to mitigate the effects of random fluctuations and highlight the underlying "level" of a series (Hyndman & Athanasopoulos, 2021; Makridakis et al., 1998).

2.2.1 Theoretical Foundations

The SMA calculates the arithmetic mean of a specific number of previous data points (n). It assumes that the most recent observations are the best indicators of the immediate future. The Simple Moving Average (SMA) calculates the arithmetic mean of a specific number of previous data points (n),which is the mathematical expression for the SMA. It suppose that recent observations are giving useful information about the immediate future, while random fluctuations can be partially smoothed out by calculating the average. The mathematical expression for the SMA is commonly written as follows (Hyndman & Athanasopoulos, 2021; Makridakis et al., 1998)

$$F_{t+1} = (A_t + A_{t-1} + A_{t-2} + \ldots + A_{t(n-1)}) / n$$

Where F_{t+1} is the forecast for the next period and A_t is the actual demand at time t.

2.2.2 Analysis of the Moving Window

The choice of n (the "window" of the average) is critical. A small n makes the model highly responsive to recent changes but also susceptible to "noise" (random error). Conversely, a large n provides superior smoothing but creates a significant time lag (Chopra & Meindl, 2016). In academic research, SMA serves as a "naive" baseline against which more complex models are compared.

2.3 Weighted Moving Average (WMA)

The Weighted Moving Average (WMA) addresses a primary weakness of the SMA: the assumption that all historical data points are equally important. . In the WMA, larger weights may be assigned to more recent observations when the analyst expects recent demand information to be more relevant for short-term forecasting (Hyndman & Athanasopoulos, 2021; Makridakis et al., 1998).

2.3.1 Weight Attribution Logic

In a WMA model, weights are assigned to each period, usually giving higher importance to the most recent data. The sum of the weights must equal one ($\Sigma w_i = 1$). The formula is:

$$F_{t+1} = \Sigma\, w_i A_{t-i+1}$$

This method allows the researcher to inject professional judgment or empirical evidence into the model. For instance, if a market shift occurred in the last month, a weight of 0.8 on A_t ensures the forecast adapts quickly.

2.3.2 Academic Significance

WMA is often preferred in industries with high volatility where the past quickly becomes obsolete. However, its effectiveness is limited by the subjective nature of weight selection, which often requires iterative testing or optimization through software (Makridakis et al., 1998).

2.4 Simple Exponential Smoothing (SES)

Simple Exponential Smoothing is a sophisticated weighting method where weight decreases exponentially as observations move further into the past. Unlike WMA, it does not require a fixed "window" of data, instead it uses a single smoothing constant, alpha (α).

2.4.1 The Smoothing Constant (α)

The core equation of SES is:

$$F_{t+1} = F_t + \alpha(A_t - F_t)$$

The value of α ranges between 0 and 1. A low α (e.g., 0.1) produces a very smooth forecast that ignores recent spikes, while a high α (e.g., 0.9) treats the most recent observation as the primary indicator of the future.

2.4.2 Strategic Application

According to Armstrong (2001), SES is highly effective for data without a clear trend or seasonality. It is mathematically efficient because it only requires the previous forecast and the most recent actual demand, making it the industry standard for large-scale inventory management systems.

2.5 Exponential Smoothing with Trend (Holt's Method)

When a time series exhibits a consistent upward or downward slope, Simple Exponential Smoothing fails because it cannot "climb" with the data, leading to a constant forecast lag. Holt's Linear Trend Model addresses this by adding a second smoothing constant, beta (β).

2.5.1 Dual-Parameter Architecture

Holt's method decomposes the forecast into two components:

Level (L_t): An estimate of the series value at the end of the period.

Trend (T_t): An estimate of the growth or decline rate.

The forecast for *m* periods ahead is calculated as:

$$F_{t+m} = L_t + m \times T_t$$

2.5.2 Smoothing the Trend

The inclusion of β allows the Holt's model to adjust the trend over time. If the trend is accelerating, a higher β allows the model to catch up. This makes Holt's model superior for growing companies or emerging markets where static averages would result in significant under-forecasting (Montgomery et al., 2015).

β controls how quickly the trend component (T_t) responds to changes in the level.

The trend equation is:

$$T_t = \beta \cdot (L_t - L_{t-1}) + (1 - \beta) \cdot T_{t-1}$$

When the trend is accelerating (i.e., the rate of growth is increasing), a higher β allows the model to catch up faster to this new rate.

Conversely, a lower β makes the trend more stable and less sensitive to short-term fluctuations.

2.6 Linear Trend Model

The Linear Trend Model moves away from smoothing techniques and utilizes the principle of Ordinary Least Squares (OLS) regression. In this model, time (*t*) is treated as the independent (predictor) variable, while demand or sales volume is treated as the dependent variable. This approach is suitable when the analyst expects a systematic upward or downward movement over time (Montgomery et al., 2015; Wooldridge, 2016).

2.6.1 Regression Principles

The relationship is defined by the linear equation (Montgomery et al., 2015; Wooldridge, 2016):

$$Y = \alpha + bt + \varepsilon$$

Where:

Y = Predicted demand or sales volume at time t

α = Y-intercept or baseline demand when t equals zero

b = Slope of the line, representing the average change in demand per time period.

ε = Random error term, , capturing unexplained variation not accounted for by the time trend.

2.6.2 Statistical Robustness

The Linear Trend Model is evaluated using the Coefficient of Determination (R^2). A high R^2 indicates that a large percentage of the demand variance is explained by the passage of time, although R^2 alone should not be interpreted as proof of forecasting accuracy. Residual diagnostics and out-of-sample forecast errors remain necessary for model validation This model is essential for long-term strategic planning, such as warehouse capacity expansion or long-term capital investment ,when demand shows a sufficiently stable trend component (Hyndman & Athanasopoulos, 2021; Montgomery et al., 2015; Wooldridge, 2016).

2.7 Linear Trend with Seasonality

In many sectors, particularly food and retail, demand does not follow a straight line but fluctuates in recurring cycles (e.g., monthly or quarterly). The Linear Trend with Seasonality model combines a deterministic trend with seasonal indices or seasonal dummy variables, allowing the model to estimate both the underlying trend and predictable seasonal deviations (Hyndman & Athanasopoulos, 2021; Makridakis et al., 1998; Wooldridge, 2016).

2.7.1 Dummy Variable Integration

This model utilizes Multiple Linear Regression by introducing "dummy variables" for each seasonal period. For a monthly series, eleven dummy variables are normally created, leaving one month as the reference category to avoid perfect multicollinearity. The model identifies seasonal “shocks” or deviations from the trend caused by recurring factors such as holidays, weather conditions, tourism patterns or cultural consumption habits (Hyndman & Athanasopoulos, 2021; Wooldridge, 2016).

$$Y_t = a + bt + c_1D_1 + c_2D_2 + ... + c_{11}D_{11} + \varepsilon_t$$

In this specification, Y_t is the predicted demand at time (t) a is the intercept or baseline demand; b is the trend coefficient, measuring the average change in demand per time period. D_1 to D_{11} are binary seasonal dummy variables that take the value 1 when a given observation belongs to the respective month and 0 otherwise. c_1 to c_{11} are the seasonal coefficients, measuring how much each month differs from the omitted reference month, and ε_t is the random error term. The omitted month becomes the benchmark against which the remaining months are interpreted (Hyndman & Athanasopoulos, 2021; Wooldridge, 2016).

2.7.2 Managerial Implications

By isolating the seasonal effect (c_i), managers can distinguish between a genuine change in market trend and a predictable seasonal peak. This prevents overreaction to temporary spikes and ensures optimal stock levels during high-demand periods (Chopra & Meindl, 2016).

2.8 Log-Linear Model

The Log-Linear model is an econometric approach used when the relationship between variables is non-linear or when the variance of the data increases with the level of demand (heteroscedasticity).

2.8.1 Logarithmic Transformation

By taking the natural logarithm (ln) of the dependent variable(Y), the researcher can transform an exponential growth pattern into a linear one:

$$ln(Y) = a + b \times t$$

where a :intercept ,b : slope, t = time

This model is particularly useful for calculating growth rates. The coefficient b in a log-linear model represents the percentage change in Y for a one-unit change in t.

2.8.2 Elasticity and Stability

As Wooldridge (2012) suggests, logarithmic models are often more robust for financial and economic data as they reduce the impact of extreme outliers and satisfy the normality assumptions required for many statistical tests.

2.9 Statistical Assumptions and Model Validation

For the regression-based models employed in this research specifically the Linear Trend Model, the Linear Trend with Seasonality, and the Log-Linear Model, the validity of the inferential results depends on the satisfaction of several fundamental econometric assumptions. According to Montgomery et al. (2015), violating these assumptions can lead to biased parameter estimates and unreliable confidence intervals.

1. **Linearity:** The model assumes a linear relationship between the independent variables (time, seasonal dummies) and the dependent variable (demand). In the Log-Linear approach, this assumption is applied to the logarithms of the data to capture approximately constant percentage growth rates rather than absolute changes (Gujarati & Porter, 2009; Wooldridge, 2016).
2. **Independence of Errors (No Autocorrelation):** Residuals should ideally be independent from one period to the next. In time-series data, this assumption is frequently violated by autocorrelation. The Durbin-Watson statistic is commonly used as an initial diagnostic for first-order autocorrelation; values close to 2.0 are usually interpreted as evidence that strong first-order autocorrelation is not present, although additional residual checks may still be required (Durbin & Watson, 1950, 1951; Montgomery et al., 2015; Wooldridge, 2016).

3. **Homoscedasticity:** This refers to the assumption that the variance of the error terms is constant across all levels of the independent variables. If the variance of the errors changes over time (Heteroscedasticity), the standard errors of the coefficients may be underestimated, leading to false claims of statistical significance (Wooldridge, 2012).
4. **Normality of Residuals:** The error terms should ideally follow an approximately normal distribution, especially when inference, confidence intervals and hypothesis tests are required. In forecasting applications, residual normality also supports the construction of prediction intervals, although forecast accuracy should still be assessed through error measures such as MAD, MAE, RMSE or MAPE (Hyndman & Athanasopoulos, 2021; Montgomery et al., 2015).

2.10 Comparative Analysis and Decision Logic

The final selection of a forecasting model is not merely a mathematical exercise, but a strategic decision based on a comprehensive comparison of the techniques analysed. Model choice should consider statistical fit, forecast accuracy, interpretability, managerial usefulness and robustness under changing market conditions. In a perishable and promotion-driven sector such as broiler production and sales, forecasting must be connected to operational decisions such as production planning, inventory control, delivery scheduling and channel allocation (Chopra & Meindl, 2019; Hyndman & Athanasopoulos, 2021).

2.10.1 Adaptive Smoothing vs. Explanatory Regression

The smoothing techniques explored in this study (SMA, WMA, and SES) are "adaptive" in nature. As noted by Chopra and Meindl (2016), these models are highly effective for tactical, short-term forecasting because they prioritize the most recent market signals.

However, they lack the structural depth to explain the "why" behind demand shifts. In contrast, the **Linear Trend with Seasonality** model provides an explanatory framework, allowing the organization to distinguish between long-term growth and recurring seasonal spikes.

2.10.2 Selection of the Optimal Model via MAD

In this study, the Linear Trend with Seasonality was identified as the superior model. Several error measures were evaluated, including **Bias (Mean Error)**which shows whether predictions are systematically above or below the actual values, **MAD (Mean Absolute Deviation)** which measures the average absolute size of the errors, **MSE (Mean Squared Error)** which gives more weight to large errors, **Standard Error** which indicates the typical distance between the observed values and the fitted regression line and **MAPE (Mean Absolute Percent Error)** which expresses the average error as a percentage of the actual values(Amazon Web Services, n.d.; eCampusOntario, 2024) . Their formulas are as follows:

Bias $= \frac{1}{n}\sum(y_i - \hat{y}_i)$,

MAD $= \frac{1}{n}\sum \mid y_i - \hat{y}_i \mid$, It.

MSE $= \frac{1}{n}\sum(y_i - \hat{y}_i)^2$,

Standard Error $= \sqrt{\frac{\sum(y_i-\hat{y}_i)^2}{n-2}}$, where $n - 2$ reflects the two degrees of freedom used to estimate the intercept and slope in simple linear regression.

MAPE $= \frac{100}{n}\sum \mid \frac{y_i-\hat{y}_i}{y_i} \mid$.(Amazon Web Services, n.d.; Forecasting error measurements and their application, 2011).

The variables used are:

n: the number of observations

i : the observation index

y_i : the actual observed value

$\hat{y}_i$: the predicted value

$y_i - \hat{y}_i$: the prediction error or residual.

The error measures also differ in their sensitivity to outliers. MSE is the most sensitive because squaring the errors gives large deviations disproportionately high weight, which can distort model evaluation when unusual observations are present (Forecasting error measurements and their application, 2011). In contrast, MAD is less affected by outliers because it uses absolute values rather than squared errors, making it a more robust and stable measure for comparing forecast models (eCampusOntario, 2024). MAPE may also become unstable when actual demand values are very small, since small denominators can inflate the percentage error (Amazon Web Services, n.d.). For this reason, MAD was preferred in this study, as it provides a more reliable assessment of typical forecasting error and is easier to interpret in the same physical units as the data, in this case kilograms.

Among these measures, MAD was chosen as the main selection criterion because it expresses forecast error in the same physical units as the data, making it easy to interpret in practical terms (eCampusOntario, 2024). By selecting the model with the lowest MAD, the study minimizes the average absolute deviation between predicted and actual demand. This is especially important in physical distribution management, because it supports a more accurate determination of safety stock levels, helps prevent stockouts, and avoids the high costs associated with overstocking (Amazon Web Services, n.d.). For these reasons, MAD was selected as the optimal criterion for the final model.

2.11 Data Processing and Computational Workflow

Before the implementation of the forecasting algorithms, a rigorous data preparation phase was executed to ensure the reliability of the output.

1. **Outlier Mitigation:** Historical datasets often contain anomalies due to external shocks. These were identified and treated to prevent them from distorting the trend line.
2. **Logarithmic Transformation:** For the Log-Linear model, the sales quantities were transformed into natural logarithms (ln). This stabilizes the variance and is particularly useful in SCM when demand exhibits a multiplicative rather than an additive structure.
3. **Software Implementation:** Computational analysis was conducted using **POM-QM for Windows** (Weiss, H. J. 2017). and the **Data Analysis Tool pack in Microsoft Excel**. These tools provided the necessary ANOVA (Analysis of Variance) tables to validate the statistical significance of the seasonal coefficients.

2.12 Impact on Supply Chain Optimization

The ultimate objective of this methodological framework is to translate statistical accuracy into operational value. By minimizing the **MAD**, the organization can optimize its procurement cycles and production scheduling. Accurate forecasting reduces the "bullwhip effect" within the supply chain, leading to improved service levels and enhanced financial performance.

Chapter 3: Time Series Forecasting Methodology and Results

3.1 Data Collection and Pre-processing Methodology

The time series at the heart of this thesis draws on primary historical data extracted from the Enterprise Resource Planning (ERP) system of PINDOS, an Agricultural Poultry Cooperative based in Ioannina. In its raw state, the dataset covered a broad array of product codes and various customer categories across the poultry sector. Working with such a sprawling set of records meant that a careful pre-processing phase was essential before any forecasting model could be applied.

To ensure the reliability and consistency of the models, the data went through a rigorous cleaning and homogenization process. The raw records were first exported into Microsoft Excel, where they were filtered and aggregated. In practical terms, this meant consolidating multiple chicken product codes into one unified category that captured total chicken sales measured in kilograms. Furthermore, sales across different professional segments were merged so as to reflect the aggregate demand within the Peloponnese region. This step of data normalization was critical — it eliminated the noise inherent in disaggregated records and produced a time series suitable for quantitative analysis (Stevenson, 2018).

Once the homogenized dataset was ready, it was imported into POM-QM for Windows (Version 5.3), a specialized decision-support tool developed by Weiss (2017). We used this software to apply a range of forecasting models and to compute key error metrics — most importantly, the Mean Absolute Deviation (MAD). The objective was to ensure that model selection rested on high-fidelity, processed operational data rather than raw, noisy inputs (Render et al., 2017).

In our analysis, four main families of time-series forecasting methods were tested: the moving average, the weighted moving average, exponential smoothing, and exponential smoothing with trend adjustment. Each method's suitability was evaluated primarily through MAD, which measures the average absolute distance between actual and forecast values. The logic is straightforward: the lower the MAD, the closer the forecasts track reality, and the better the method performs (Heizer et al., 2020; Stevenson, 2021).

3.2 Moving Average Method

The moving average is among the most intuitive forecasting techniques. It works by computing the arithmetic mean of a specified number of previous observations, effectively smoothing out random fluctuations and providing a short-term forecast. A key assumption here is that all recent observations contribute equally to the next prediction — there are no differentiated weights (Makridakis et al., 1998; Stevenson, 2021). While this simplicity is a strength in terms of implementation, it also means the method cannot prioritize the latest data over older values.

In the Excel file and through POM-QM, two versions of the method were examined to gauge how the number of periods affects accuracy.

3.2.1 Two-Period Moving Average

In the two-period version, the forecast for each period is simply the average of the two immediately preceding actual values. It is the most responsive variant of the moving average, since it considers only the two most recent data points. According to the results obtained from the Excel file, this method produced the following outputs:

Bias (Mean Error): 2,860.136

MAD: 20,826.49

MSE: 677,186,000

Standard Error: 26,402.71

MAPE: 0.10066

Forecast for the next period: 270,397

What stands out is that while the method provides a reasonable degree of smoothing, the MAD value remains notably higher than those produced by other techniques tested in this study. In practical terms, this means that despite being easy to implement and understand, the two-period moving average was not the optimal approach for capturing the dynamics of this particular time series.

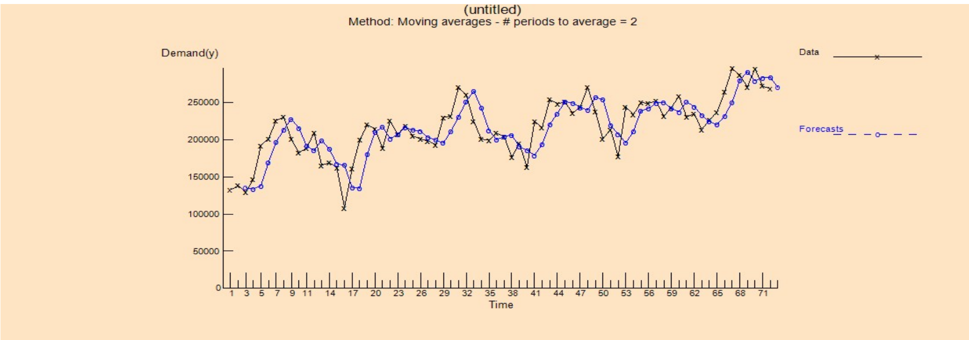

Figure 2. POM-QM chart output for the two-period moving average.

3.2.2 Three-Period Moving Average

The three-period moving average takes a broader view by using the average of the three preceding observations to generate each forecast. In theory, averaging over more periods should smooth out noise more effectively. The Excel results for this variant yielded the following:

Bias (Mean Error): 4,100.354

MAD: 23,588.81

MSE: 827,287,600

Standard Error: 29,188.74

MAPE: 0.11280

Forecast for the next period: 278,847.3

Increasing the number of periods did smooth the series further, but it came at a cost: the method lost responsiveness to recent changes. A closer look at the numbers reveals that MAD actually increased compared to the two-period variant. This tells us that including one additional period did not improve forecasting accuracy — it moved the forecast further away from the true dynamics of the data.

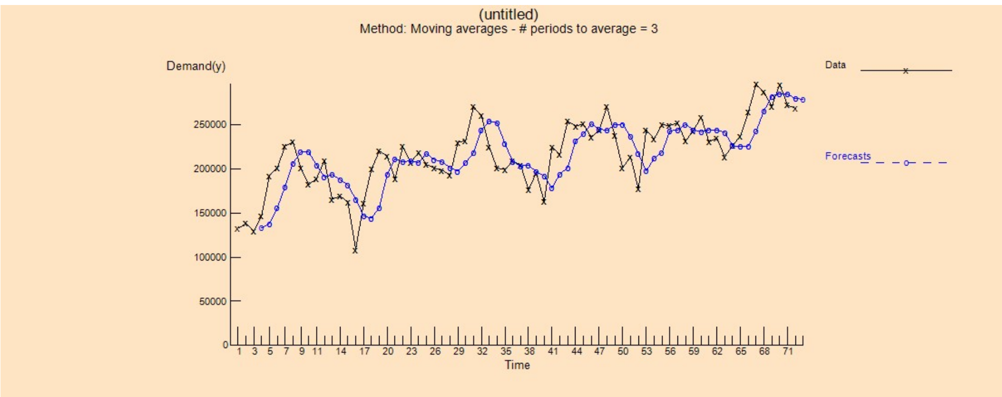

Figure 3. POM-QM chart output for the three-period moving average.

3.2.3 Interpretation of the Method's Results

Overall, the moving average method demonstrated moderate performance when applied to this dataset. Its better-performing version turned out to be the two-period moving average, which exhibited a lower MAD than the three-period alternative. Nevertheless, both variants underperformed relative to methods that assign greater importance to the most recent observations — a quality that becomes critical when the time series exhibits variation or does not behave in a fully stable manner (Heizer et al., 2020). In short, the moving average serves as a useful baseline, but the data clearly calls for something more adaptive.

3.3 Weighted Moving Average Method

The weighted moving average extends the simple moving average by assigning different levels of importance to past observations. Rather than treating all previous values equally, it gives greater weight to the most recent data points, which are generally considered more representative of the current trend and underlying conditions (Render et al., 2018; Stevenson, 2021). This makes intuitive sense: in a market environment that can shift quickly, yesterday's data is often more informative than data from several months ago.

In our analysis, five different weight combinations were tested through POM-QM to see which allocation best captured the pattern in the sales data.

3.3.1 Weighted Moving Average with Weights 0.5 / 0.5

The first weight combination splits emphasis equally between the two most recent periods. The performance measures were:

Bias: 2,860.136

MAD: 20,826.49

MSE: 677,186,000

Standard Error: 26,402.71

MAPE: 0.10066

Forecast for the next period: 270,397

It is worth noting that this result is mathematically identical to the two-period simple moving average, which makes perfect sense — when both periods receive equal weight, the weighted moving average reduces to the ordinary average. This serves as a useful sanity check rather than a new finding.

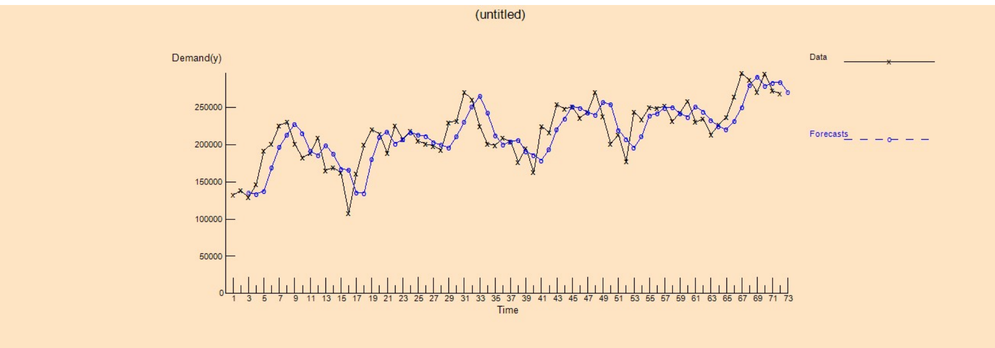

Figure 4. POM-QM chart output for weights 0.5 / 0.5.

3.3.2 Weighted Moving Average with Weights 0.6 / 0.4

Shifting more emphasis toward the most recent period, this combination allocated 60% of the weight to the latest observation and 40% to its predecessor. The results were:

Bias: 2,660.269

MAD: 20,229.89

MSE: 644,458,100

Standard Error: 25,756.80

MAPE: 0.09808

Forecast for the next period: 270,002

Forecast accuracy improved relative to the equal-weight specification, as reflected in the lower MAD. This already hints at a pattern: the series rewards methods that pay closer attention to its most recent behaviour.

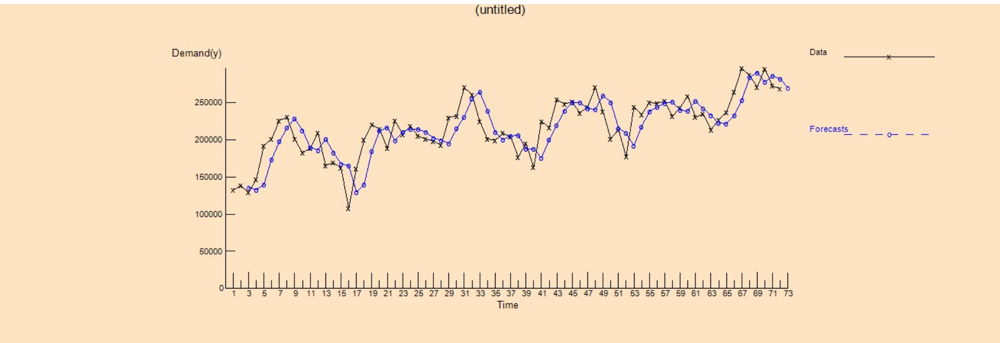

Figure 5. POM-QM chart output for weights 0.6 / 0.4.

3.3.3 Weighted Moving Average with Weights 0.7 / 0.3

Pushing the weight further toward the latest period, the 0.7 / 0.3 combination produced the following:

Bias: 2,460.402

MAD: 19,733.38

MSE: 624,574,400

Standard Error: 25,356.35

MAPE: 0.09597

Forecast for the next period: 269,607

The downward trend in MAD continues here, which reinforces the observation that this time series responds better when recent data receives a heavier weight. Each incremental shift toward the latest observation has yielded a measurable improvement in accuracy.

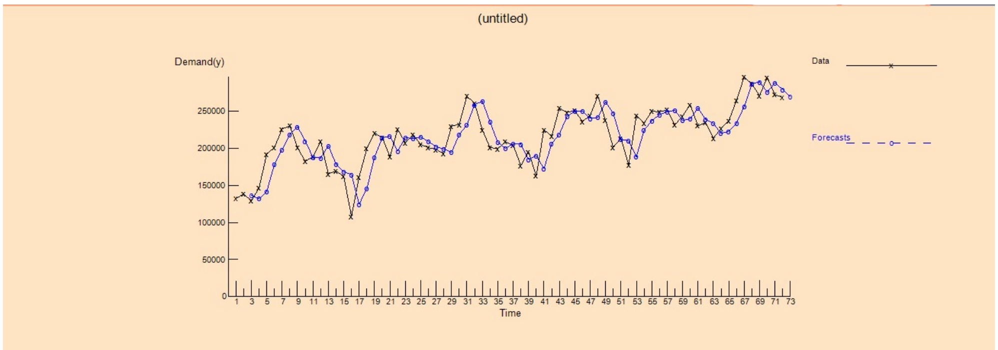

Figure 6. POM-QM chart output for weights 0.7 / 0.3.

3.3.4 Weighted Moving Average with Weights 0.8 / 0.2

With 80% of the weight on the most recent observation and only 20% on the period before it, this specification produced:

Bias: 2,260.534

MAD: 19,529.86

MSE: 617,535,900

Standard Error: 25,213.07

MAPE: 0.09509

Forecast for the next period: 269,212

This turned out to be the best-performing weighted moving average among all the alternatives tested. The 0.8 / 0.2 combination achieved the lowest MAD within this family of models, suggesting that the optimal balance for this dataset lies in placing strong — but not total — emphasis on the most recent value.

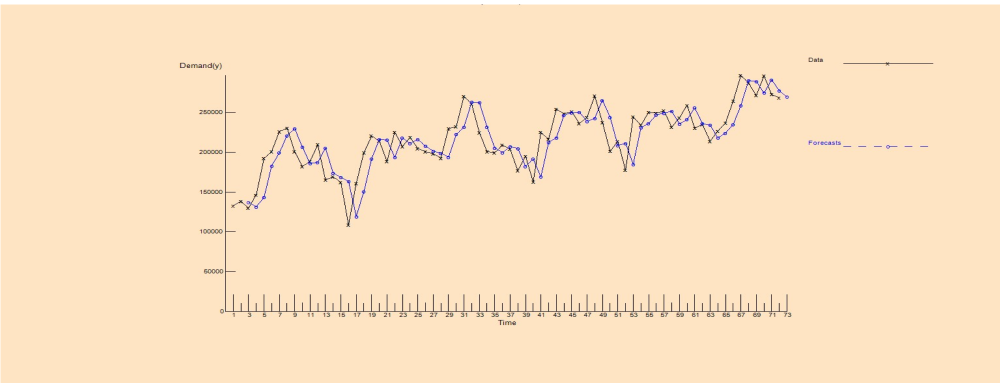

Figure 7. POM-QM chart output for weights 0.8 / 0.2.

3.3.5 Weighted Moving Average with Weights 0.9 / 0.1

Finally, an extreme weighting scheme was tested, assigning 90% to the latest observation and only 10% to the one before it. The results were:

Bias: 2,060.668

MAD: 19,649.13

MSE: 623,341,600

Standard Error: 25,331.31

MAPE: 0.09558

Forecast for the next period: 268,817

Although the method remained fairly accurate, the MAD increased slightly compared with the 0.8 / 0.2 version. This is a telling result: pushing too much emphasis onto a single observation introduces excessive sensitivity to period-to-period noise, and the marginal gain from recency flips into a marginal loss. There is, in other words, a sweet spot.

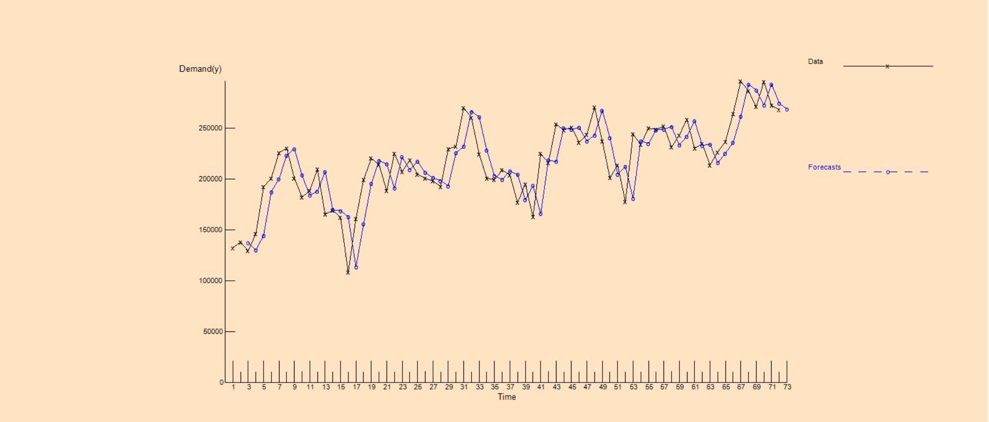

Figure 8. POM-QM chart output for weights 0.9 / 0.1.

3.3.6 Interpretation of the Method's Results

The analysis of the different weighting schemes reveals a clear pattern: accuracy improves as the weight assigned to the most recent observation increases, but only up to a certain point. Based on both the Excel file and the POM-QM results, the best-performing version was the weighted moving average with weights 0.8 / 0.2, which achieved a MAD of 19,529.86. Beyond that threshold — at 0.9 / 0.1 — accuracy begins to deteriorate slightly. For this time series, the weighted moving average outperformed the simple moving average because it more effectively incorporated the relative importance of the latest data (Heizer et al., 2020). Still, it remained to be seen whether exponential smoothing could do even better.

3.4 Exponential Smoothing Method

Exponential smoothing is one of the most widely used forecasting techniques in practice, and for good reason. It assigns greater weight to recent observations without completely discarding older data — the influence of past values declines exponentially over time. This decay is controlled by the smoothing constant α (alpha), which ranges from 0 to 1. A larger α makes the method more responsive to recent shifts, while a smaller α produces a smoother, more stable forecast (Makridakis et al., 1998; Stevenson, 2021).

In our analysis, multiple α values ranging from 0.00 to 0.99 were tested through POM-QM. The goal was simple: find the α value that minimizes MAD, thereby producing the most accurate forecasts for this specific dataset.

3.4.1 Results for Simple Exponential Smoothing

After testing the full range of smoothing constants, the best performance emerged at α = 0.83. The results were as follows:

Bias: 2,328.134

MAD: 19,295.92

MSE: 611,494,400

Standard Error: 25,084.24

MAPE: 0.09417

Forecast for the next period: 269,661.9

This is the lowest MAD among all the principal time-series forecasting methods examined in the POM-QM file, which signals that simple exponential smoothing with a relatively high smoothing constant provided the best overall fit to the available data within the smoothing family of methods.

It is worth noting how MAD declined as α increased. For instance, at α = 0.80 the MAD stood at 19,334.67; at α = 0.81, it dropped to 19,320.41; at α = 0.82, it reached 19,305.89; and at α = 0.83, it hit the minimum value of 19,295.92. This gradual improvement shows that the time series responds strongly to a method that places heavy emphasis on the most recent observations — a pattern consistent with what we observed in the weighted moving average experiments.

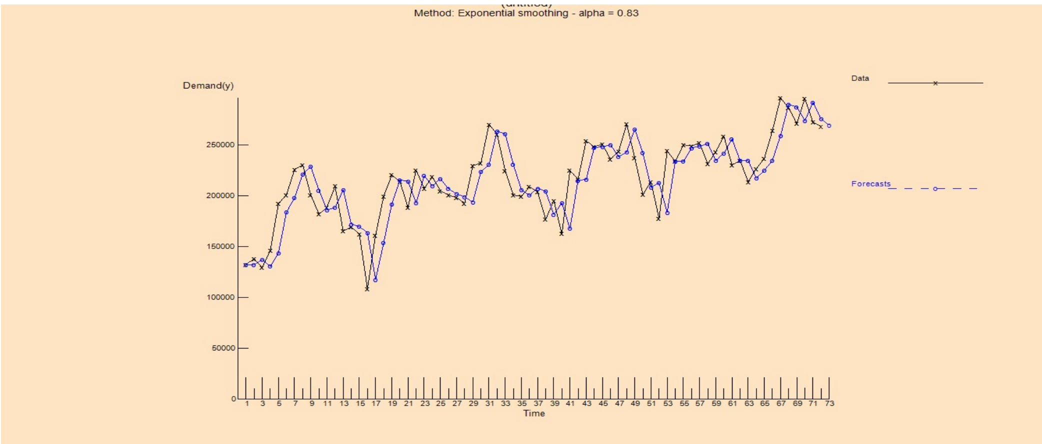

Figure 9. POM-QM chart output for simple exponential smoothing (α = 0.83).

3.4.2 Exponential Smoothing with Trend

The analysis also examined trend-adjusted exponential smoothing to determine whether explicitly incorporating both level and trend components could improve forecast accuracy. This variant, sometimes referred to as Holt's method, uses two smoothing constants: α for the level and β for the trend.

From the worksheet results, the combination α = 0.1 and β = 0.1 produced the following values:

Bias: 16,000.11

MAD: 26,069.76

MSE: 1,058,264,000

Standard Error: 32,999.07

MAPE: 12.11%

Forecast for the next period: 258,467.4

In addition, for the combination α = 0.3 and β = 0.1, the results were:

Bias: 4,975.936

MAD: 22,688.74

MSE: 774,291,800

Standard Error: 28,226.50

MAPE: 10.94%

Forecast for the next period: 275,657.5

Accordingly in the present study, a grid search procedure was applied in order to select the most appropriate parameter values, and the optimal specification was identified as the one yielding the lowest MAD. We can observe the results in the table below

Exponential Smoothing with Trend

α \ β	0.1	0.3	0.5	0.7	0.9
0.1	26.069,76	25.617,94	25.173,18	24.910,03	24.753,46
0.3	22.688,74	22.244,01	21.408,31	20.697,53	20.190,14
0.5	21.500,91	20.905,73	19.880,93	19.517,49	19.716,66
0.7	20.050,15	20.396,17	20.978,06	21.719,74	22.670,09
0.9	20.253,50	21.893,08	23.436,87	24.995,24	26.818,76

Across all 25 combinations of smoothing constants tested via POM-QM and the Excel file, the parameters α = 0.5 (level smoothing) and β = 0.7 (trend smoothing) yielded the most accurate forecast, minimizing the MAD to 19,517.49. While this represents a significant improvement over the initial trend-adjusted specifications, it remains clearly worse than the simple exponential smoothing model with α = 0.83. The conclusion is straightforward: for this dataset, the explicit inclusion of a trend component did not improve accuracy. The series apparently does not exhibit a strong enough trend to justify the added model complexity.

The 25 trend-adjusted combinations tested are illustrated in Figures 10 through 35 below.

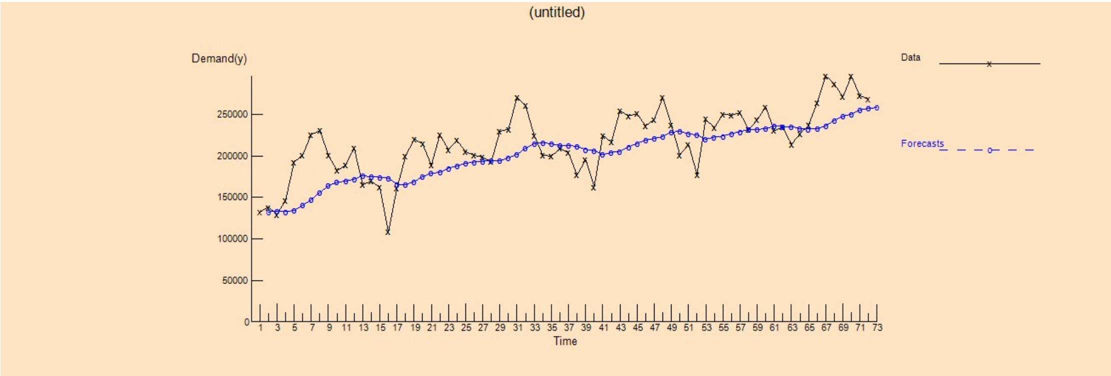

Figure 10. Trend-adjusted exponential smoothing (α = 0.1, β = 0.1)

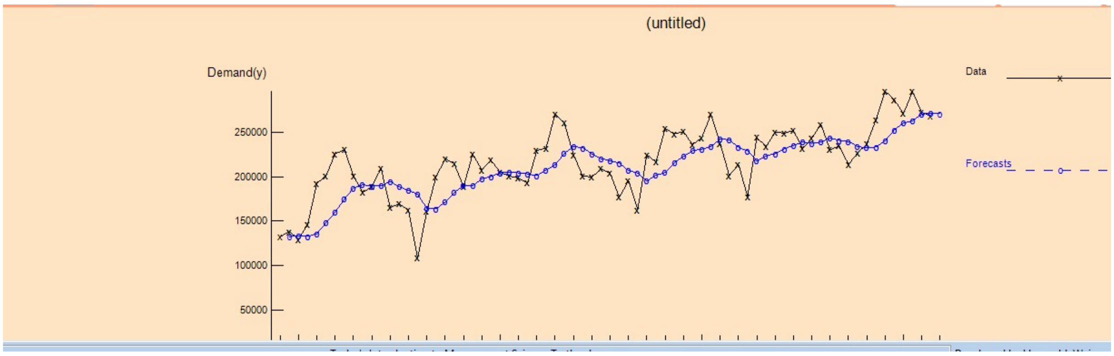

Figure 11. Trend-adjusted exponential smoothing (α = 0.2, β = 0.1)

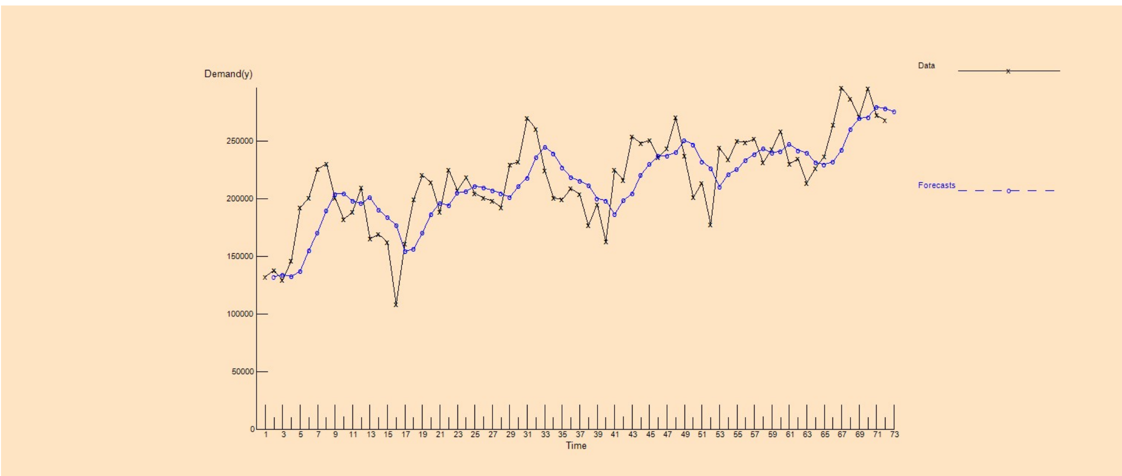

Figure 12. Trend-adjusted exponential smoothing (α = 0.3, β = 0.1)

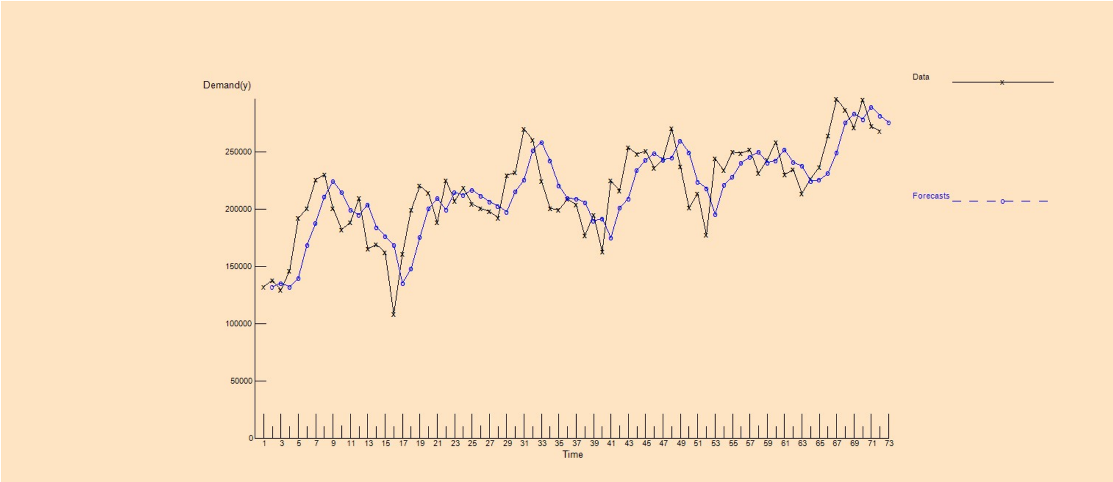

Figure 13. Trend-adjusted exponential smoothing (α = 0.5, β = 0.1)

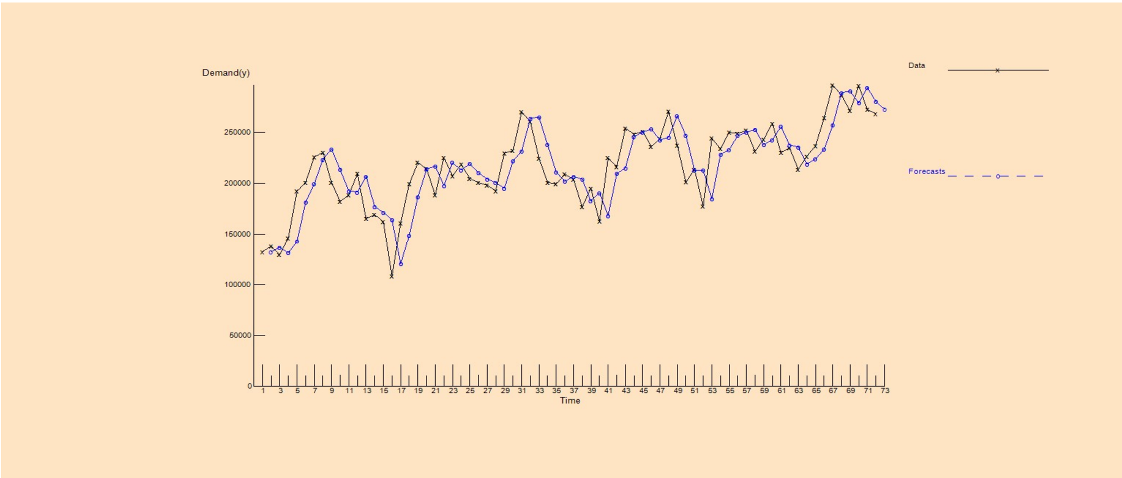

Figure 14. Trend-adjusted exponential smoothing (α = 0.5, β = 0.3)

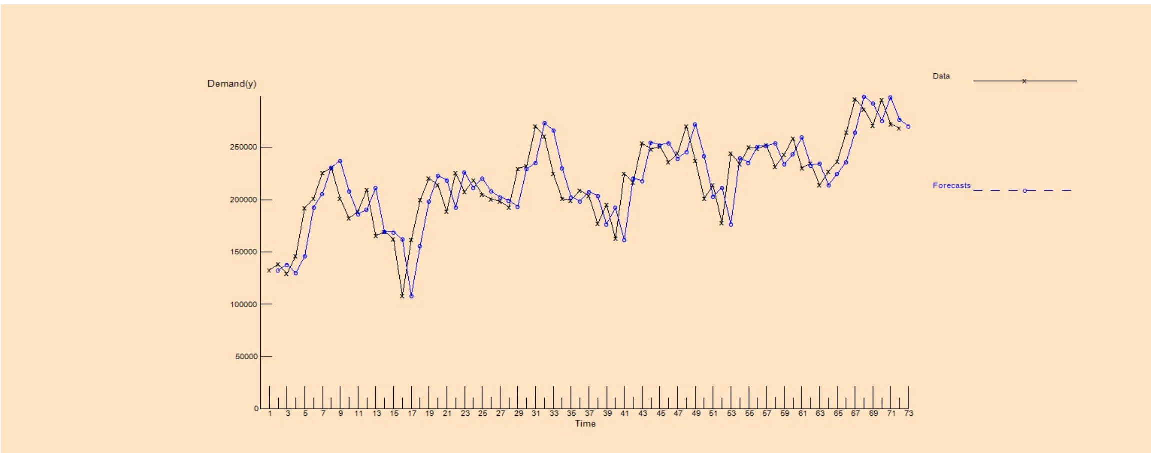

Figure 15. Trend-adjusted exponential smoothing (α = 0.5, β = 0.5)

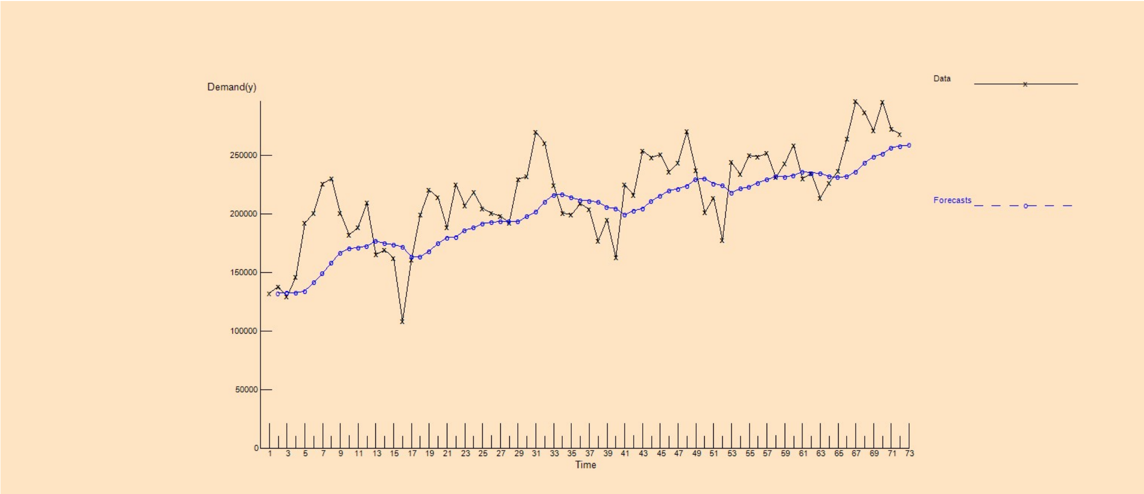

Figure 16. Trend-adjusted exponential smoothing (α = 0.5, β = 0.7)

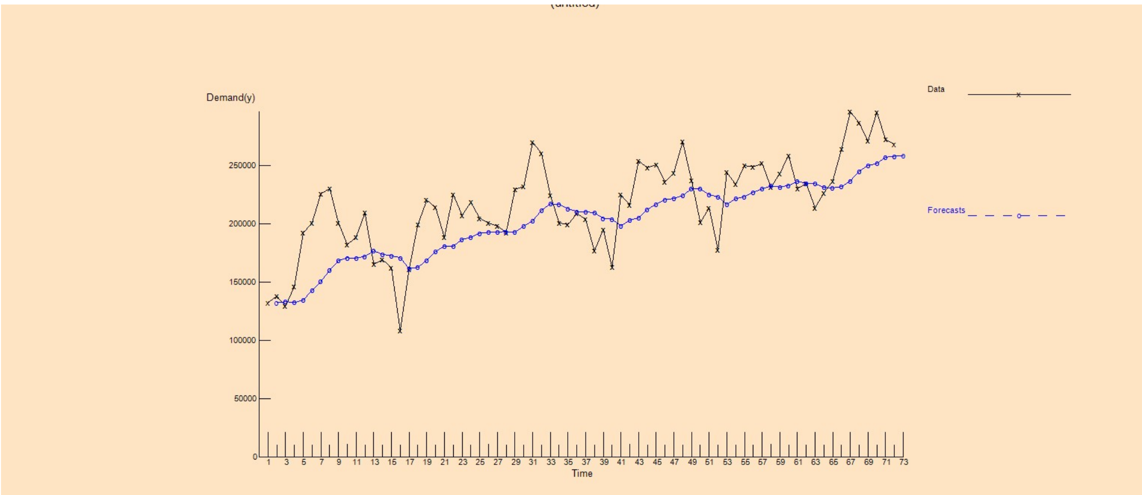

Figure 17. Trend-adjusted exponential smoothing (α = 0.5, β = 0.9)

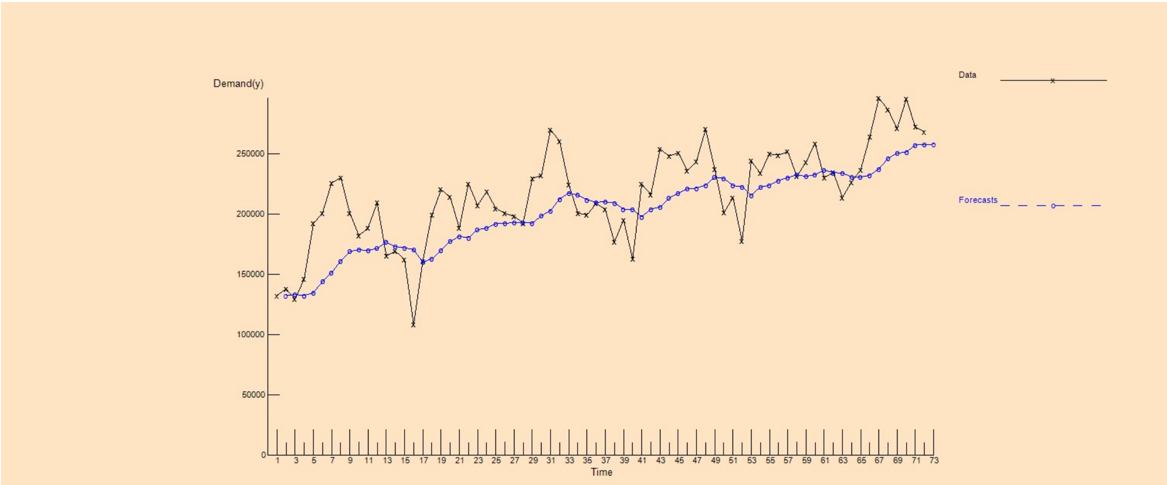

Figure 18. Trend-adjusted exponential smoothing (α = 0.7, β = 0.1)

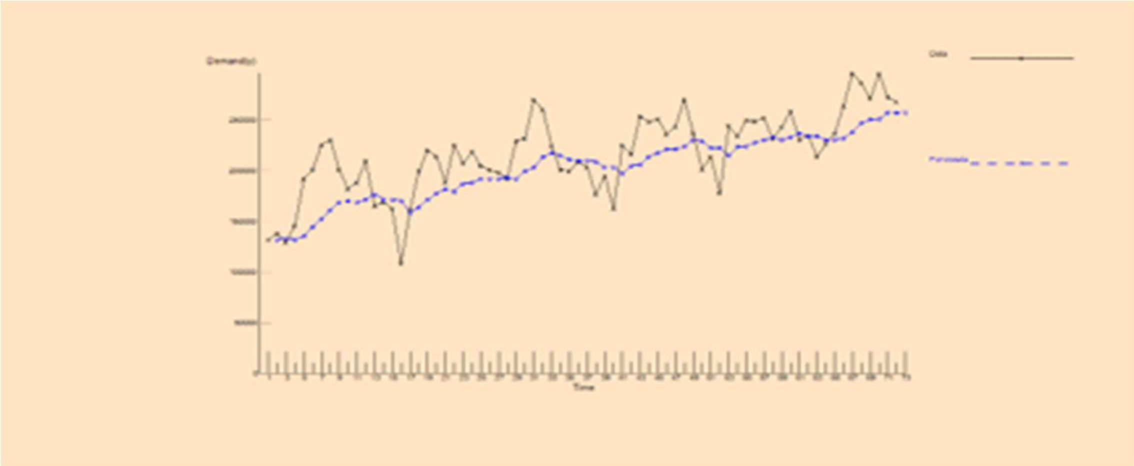

Figure 19. Trend-adjusted exponential smoothing (α = 0.7, β = 0.3)

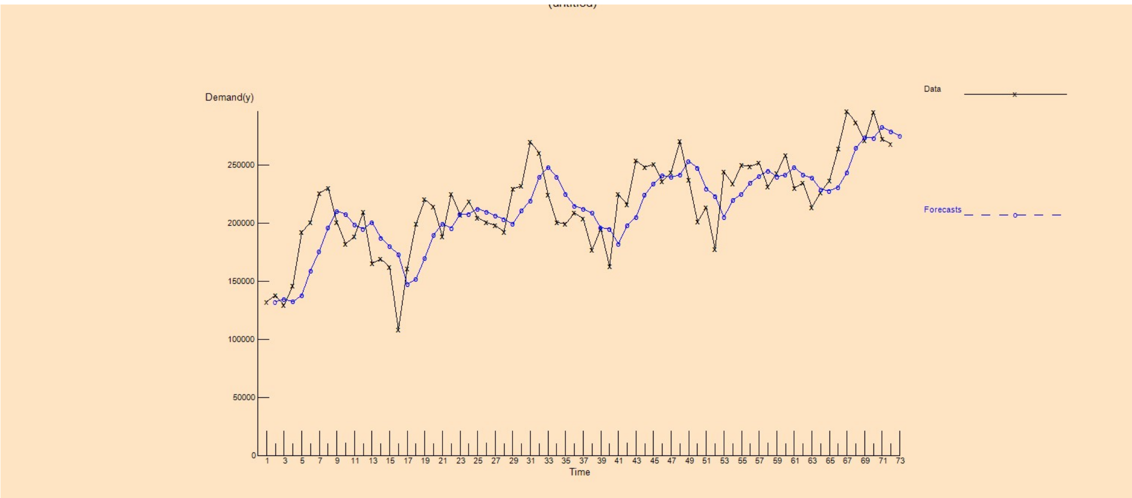

Figure 20. Trend-adjusted exponential smoothing (α = 0.7, β = 0.5)

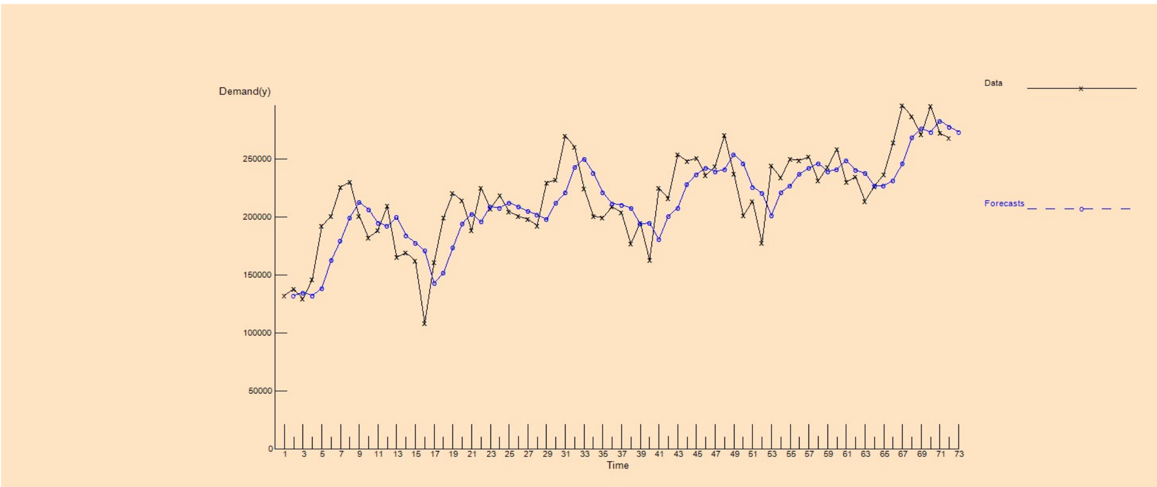

Figure 21. Trend-adjusted exponential smoothing (α = 0.7, β = 0.7)

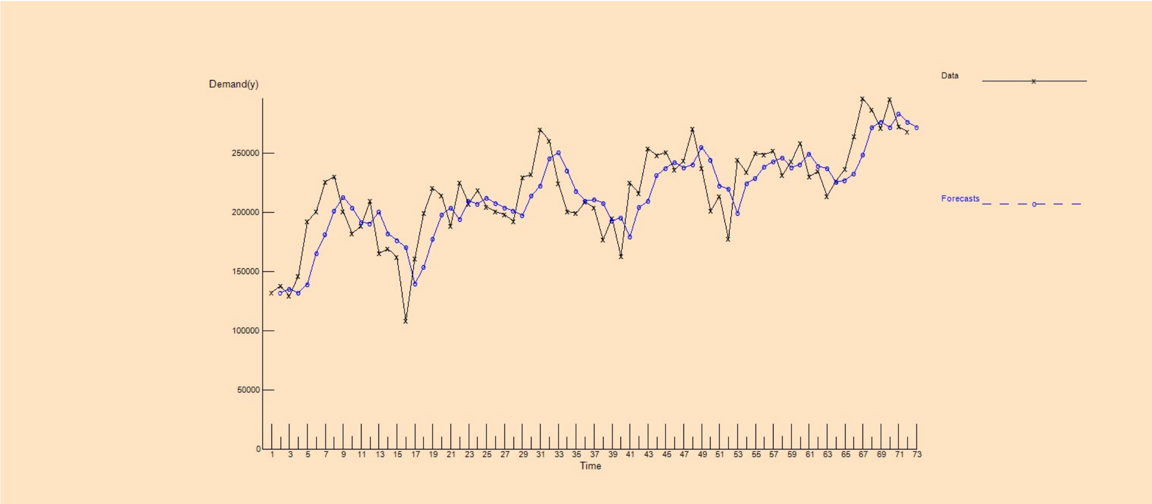

Figure 22. Trend-adjusted exponential smoothing (α = 0.7, β = 0.9)

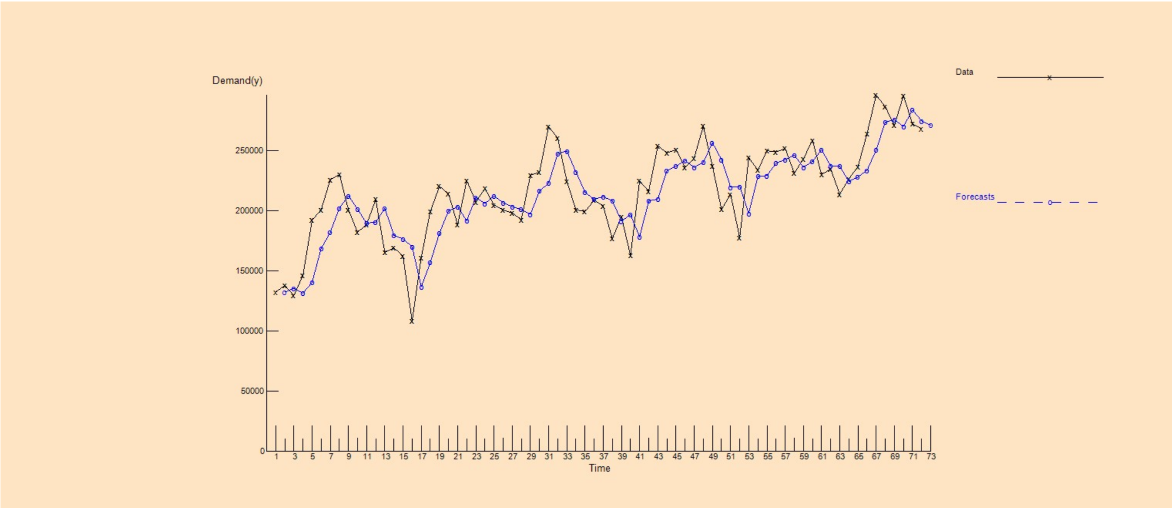

Figure 23. Trend-adjusted exponential smoothing (α = 0.9, β = 0.1)

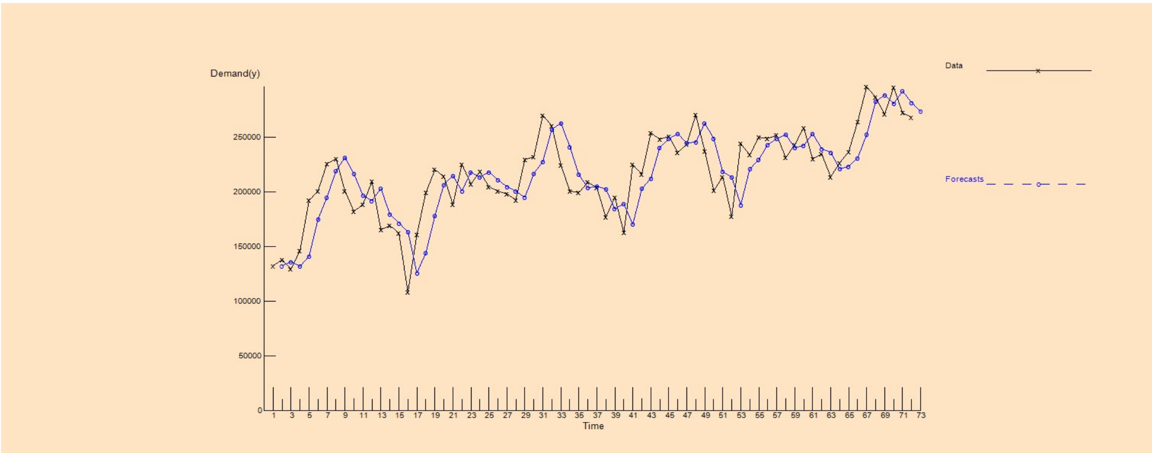

Figure 24. Trend-adjusted exponential smoothing (α = 0.9, β = 0.3)

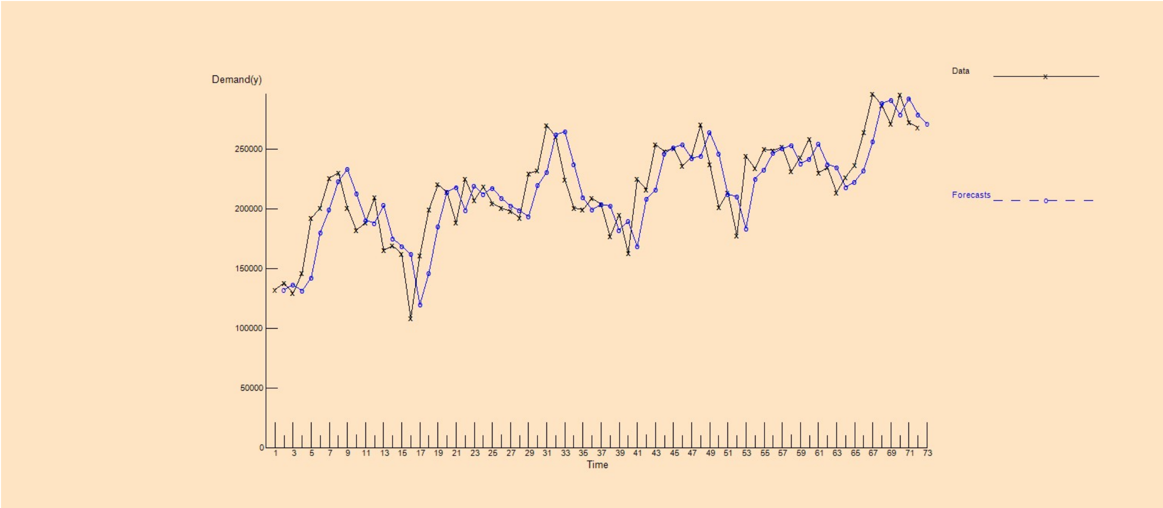

Figure 25. Trend-adjusted exponential smoothing (α = 0.9, β = 0.5)

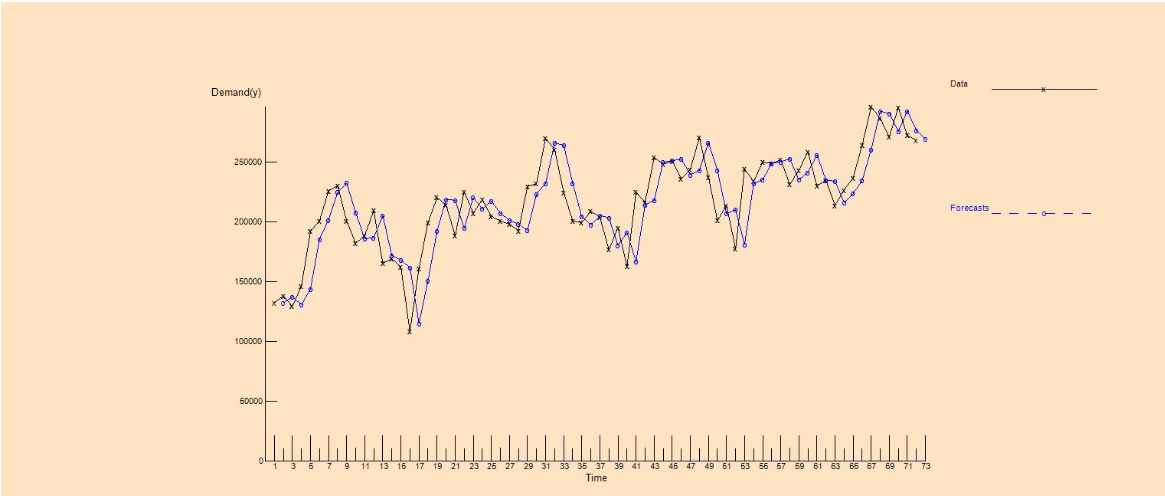

Figure 26. Trend-adjusted exponential smoothing (α = 0.9, β = 0.7)

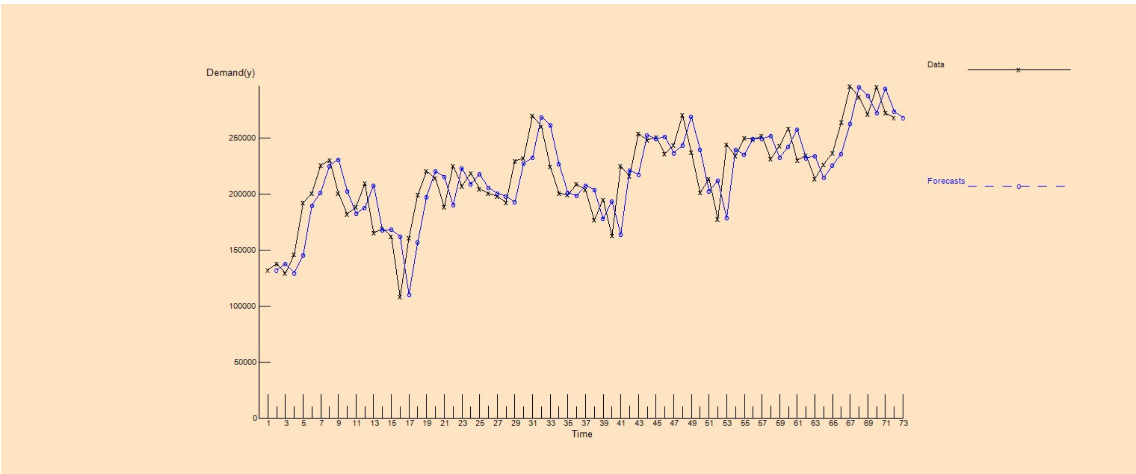

Figure 27. Trend-adjusted exponential smoothing (α = 0.9, β = 0.9)

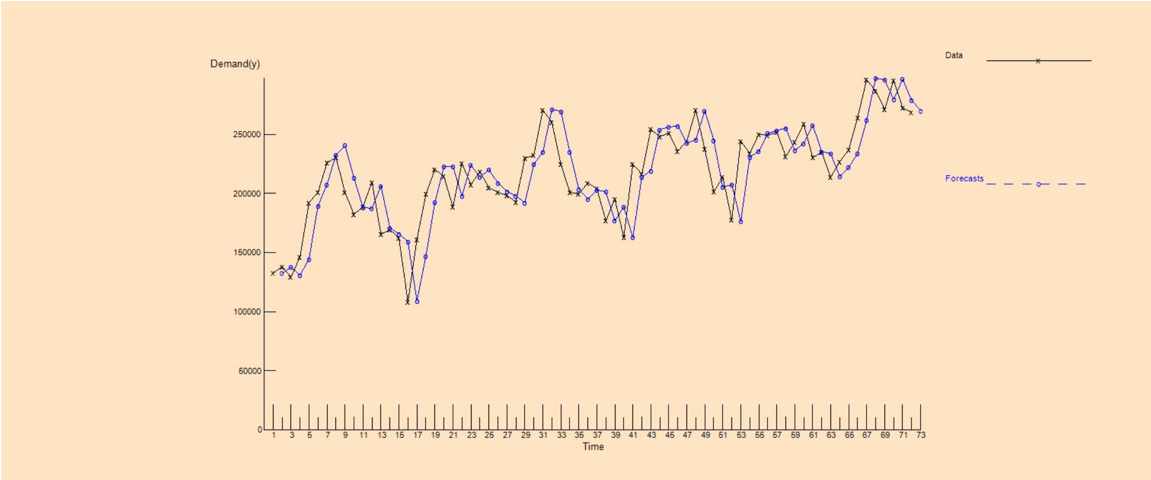

Figure 28. Trend-adjusted exponential smoothing (α = 0.1, β = 0.3)

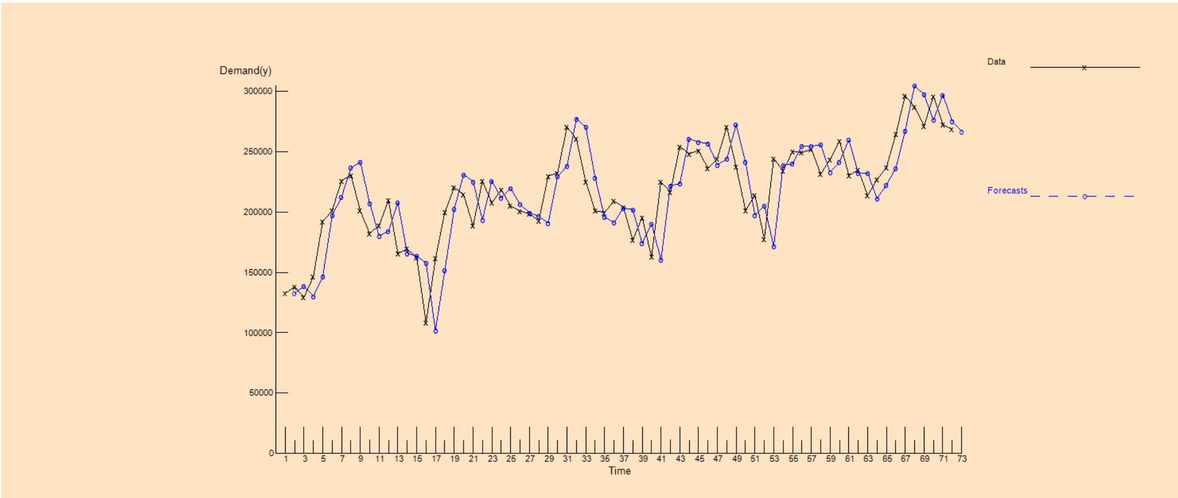

Figure 29. Trend-adjusted exponential smoothing (α = 0.1, β = 0.5)

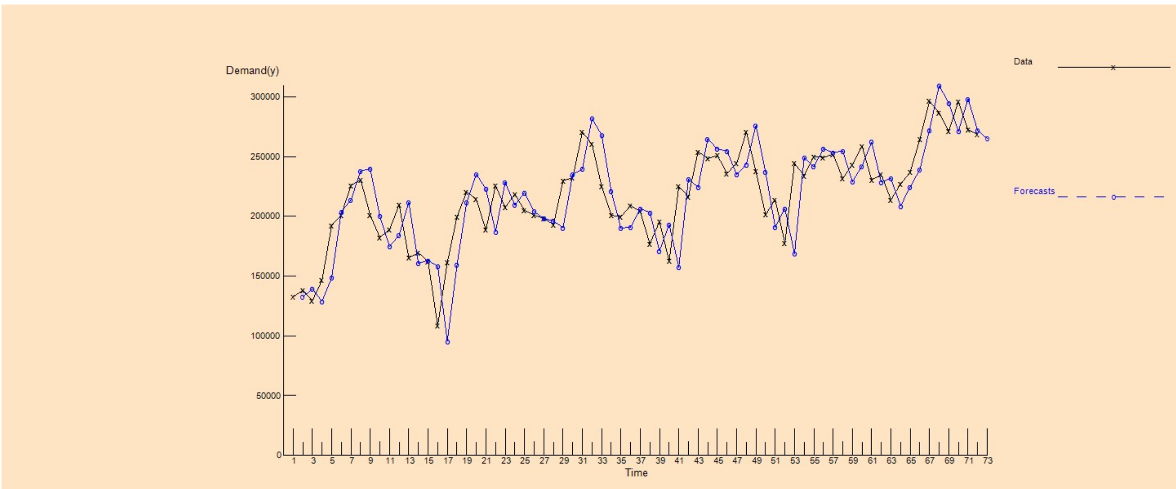

Figure 30. Trend-adjusted exponential smoothing (α = 0.1, β = 0.7)

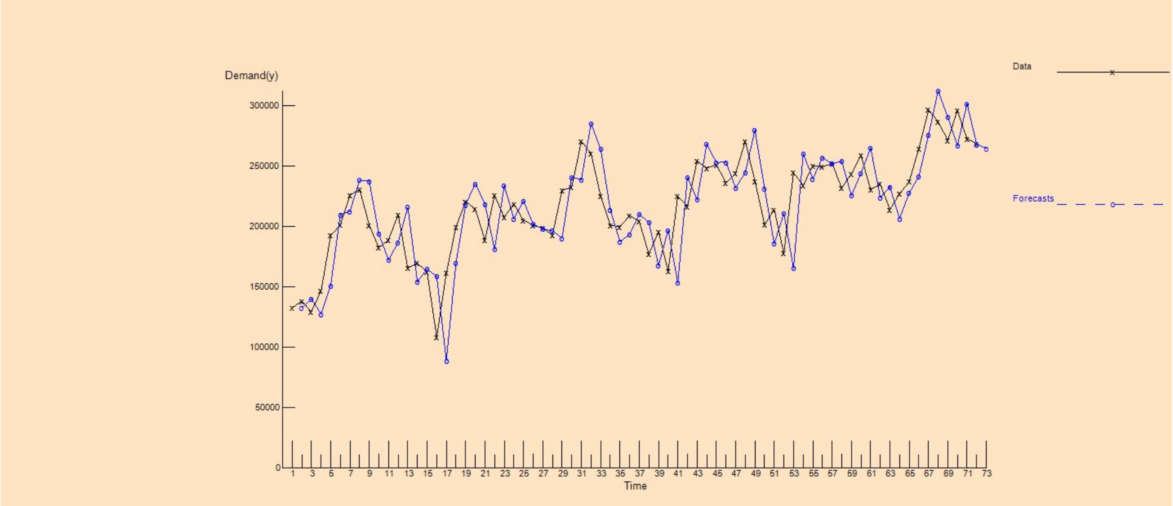

Figure 31. Trend-adjusted exponential smoothing (α = 0.1, β = 0.9)

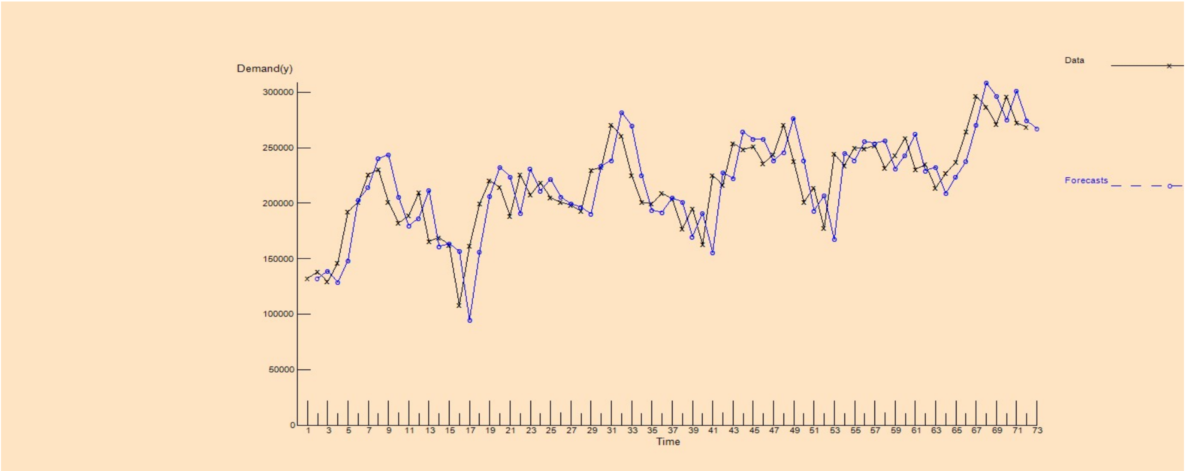

Figure 32. Trend-adjusted exponential smoothing (α = 0.3, β = 0.3)

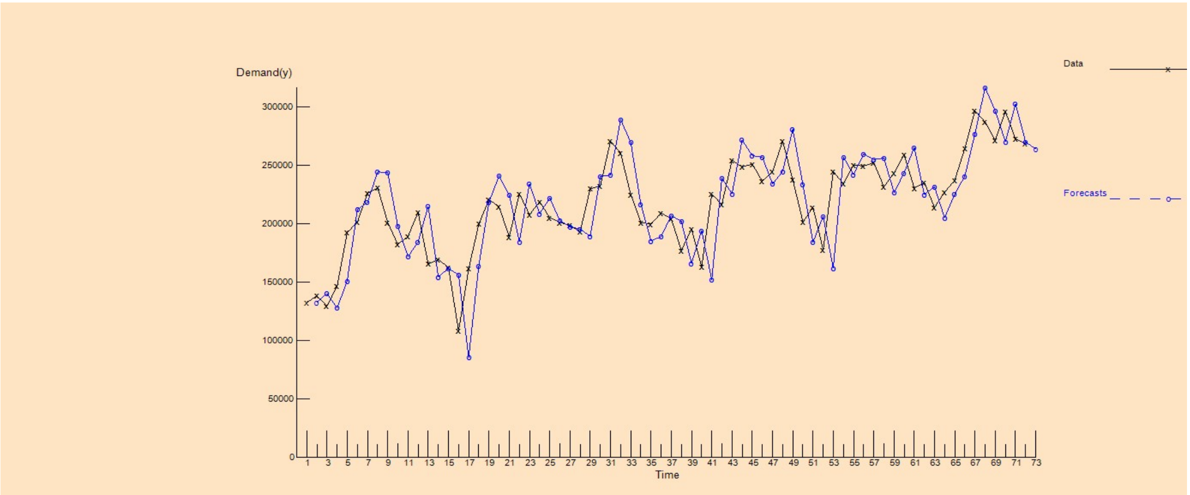

Figure 33. Trend-adjusted exponential smoothing (α = 0.3, β = 0.5)

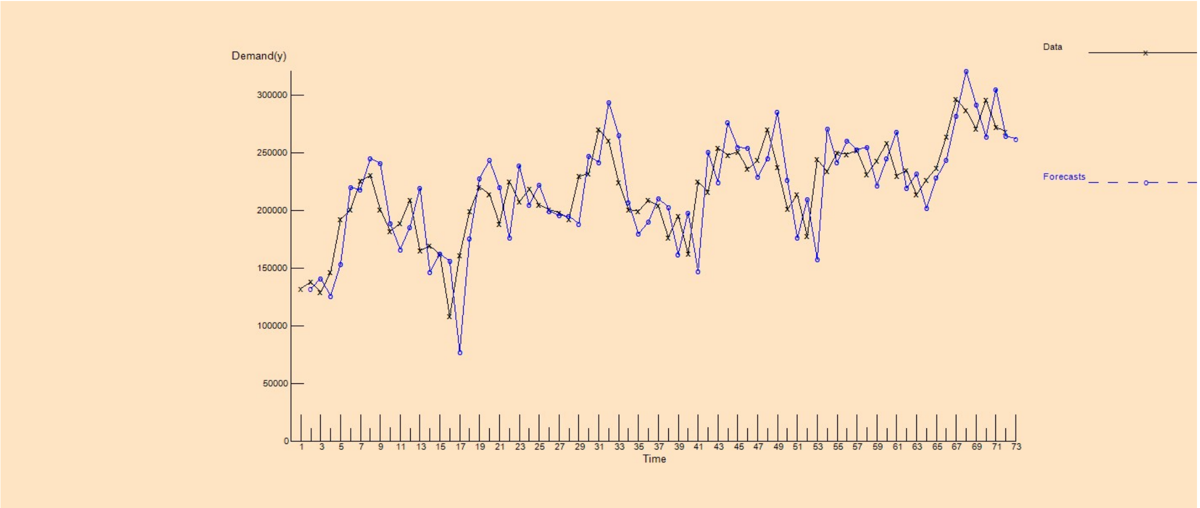

Figure 34. Trend-adjusted exponential smoothing (α = 0.3, β = 0.7)

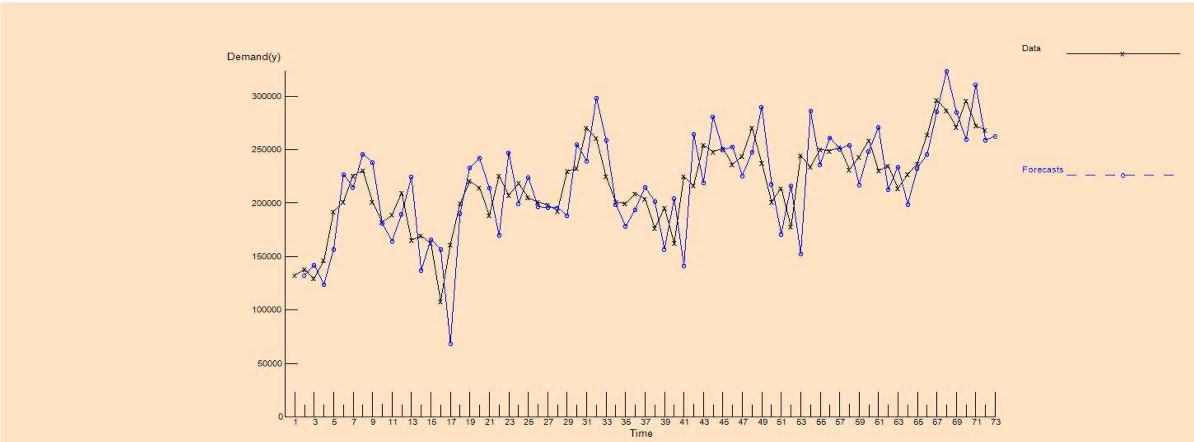

Figure 35. Trend-adjusted exponential smoothing (α = 0.3, β = 0.9)

3.4.3 Interpretation of the Method's Results

Simple exponential smoothing proved to be the most effective time-series method in the POM-QM analysis. The low MAD of 19,295.92 and the relatively modest MAPE indicate that this method tracks the fluctuations of the series better than both the simple moving average and the weighted moving average. The fact that the optimal α value is as high as 0.83 reinforces a recurring theme in this chapter: the most recent information is especially important for forecasting the next period in this dataset. Meanwhile, the trend-adjusted variant, despite offering theoretical appeal, did not manage to beat the simpler model ,a reminder that added complexity does not always translate into added accuracy.

3.5 Regression-Based Forecasting Models

To complement the smoothing techniques explored above, three regression-based forecasting specifications were estimated using the dataset in the file "linear regression excel.xlsx." The motivation behind this step was to test whether incorporating a deterministic trend and monthly seasonality could improve forecast accuracy beyond what the POM-QM time-series methods achieved. For comparing these regression models, we relied primarily on MAD, while R^2 and adjusted R^2 served as supporting indicators of goodness of fit (Makridakis et al., 1998; Hyndman & Athanasopoulos, 2021).

The regression sample consists of 72 monthly observations of the variable "Quantity in kilograms," spanning the period from 2019 to 2024. Time was coded sequentially from 1 to 72. In the seasonal specifications, monthly dummy variables from February through December were introduced, with January serving as the reference month. This structure was designed to capture both the long-run upward trend and the recurring intra-year seasonal pattern that is visible in the historical sales data.

3.5.1 Overview of the Regression Specifications

Three alternative regression formulations were examined: a simple linear trend model, a linear trend model with monthly seasonal dummy variables, and a log-linear trend model with seasonality. Their principal outputs are summarized in Table 3.5.1.

Model	MAD	Forecast Next Period	R^2	Adjusted R^2
Linear trend model	21,727.90	266,941.73	0.522	0.515
Linear trend with seasonality	12,690.21	248,425.05	0.847	0.815
Log-linear trend with seasonality	13,631.13	247,746.47	0.814	0.776

Table 3.5.1. Summary of regression-based forecasting models.

3.5.2 Linear Trend Model

From the output of excel tool we create the following results

SUMMARY OUTPUT

Regression statistics	
Multiple R	0,722282794
R Square	0,521692434
Adjusted R square	0,514859469
Standard error	27657,13412
Sample size	72

ANALYSIS OF VARIANCE

	Degrees of freedom	*SS*	*MS*	*F*	*Significance F*
Regression	1	58400918759	58400918759	76,34934715	8,01E-13
Residual	70	53544194753	764917067,9		
Total	71	1,11945E+11			

	Coefficients	*Standard error*	*t*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	166903,3876	6587,350199	25,33695378	5,52227E-37	153765,3	180041,4
TIME	1370,388199	156,8342626	8,737811348	8,00788E-13	1057,592	1683,184

The first specification estimates the straightforward relationship $Q_t = a + b \cdot t$, where Q_t denotes monthly quantity in kilograms and t is a sequential time index. The estimated trend coefficient is positive and statistically significant ($\beta = 1{,}370.39$, $p < 0.001$), confirming an upward movement in the sales series over time. However, the model's explanatory power is only moderate $R^2 = 0.522$ and adjusted $R^2 = 0.515$, because it captures trend but completely ignores monthly seasonality.

MAD: 21,727.90

Forecast for the next period (t = 73): 266,941.73 kg

From a forecasting perspective, the simple linear trend model performs better than the three-period moving average, but it is materially weaker than the best smoothing specifications and, more importantly, weaker than the seasonal regression models. Its main limitation is the omission of the pronounced monthly seasonal structure that is clearly visible in the historical data.

3.5.3 Linear Trend Model with Seasonality

SUMMARY OUTPUT

Regression statistics	
Multiple R	0,920063498
R square	0,84651684
Adjusted R square	0,815299926
Standard error	17065,02506
Sample size	72

ANALYSIS OF VARIANCE

	Degrees of freedom	*SS*	*MS*	*F*	*Significance F*
Regression	12	94763423770	7896951981	27,11725	1,31268E-19
Residual	59	17181689742	291215080,4		
Total	71	1,11945E+11			

	Coefficients	*Standard error*	*t*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	156915,1051	7601,99974	20,64129314	1,12E-28	141703,5388	172126,6715
TIME	1253,560857	98,13321721	12,77407276	1,24E-18	1057,196743	1449,924971
FEBRUARY	-10126,87711	9852,985516	-1,027797827	0,30824	-29842,65559	9588,901372
MARCH	-12755,66838	9854,45148	-1,294406736	0,200568	-32474,38024	6963,043485
APRIL	-30416,97757	9856,894268	-3,085858156	0,003089	-50140,57744	-10693,3777
MAY	14138,42167	9860,313155	1,433871466	0,156888	-5592,019376	33868,86272
JUNE	22588,69672	9864,707125	2,289849707	0,025623	2849,463354	42327,93008
JULY	49564,85086	9870,074877	5,021729975	5,03E-06	29814,87665	69314,82507
AUGUST	43647,9141	9876,414822	4,419408752	4,3E-05	23885,25369	63410,57452
SEPTEMBER	25609,04998	9883,725091	2,591032201	0,01204	5831,761756	45386,33821
OKTOBER	21581,73646	9892,003531	2,18173562	0,033125	1787,883113	41375,5898

NOVEMBER	17645,53477	9901,247714	1,782152642	0,07987	-2166,816145	37457,88568
DECEMBER	29553,08391	9911,454938	2,981709961	0,004161	9720,30839	49385,85943

The second specification adds monthly dummy variables to the deterministic trend, allowing the model to capture seasonal demand patterns. This augmentation dramatically improves the fit: R^2 rises to 0.847 and adjusted R^2 to 0.815. The time trend remains positive and highly significant ($\beta = 1{,}253.56$, $p < 0.001$), while the seasonal coefficients reveal strong positive deviations during the summer months — especially July and August — and a statistically significant negative deviation in April.

MAD: 12,690.21

Forecast for the next period (t = 73): 248,425.05 kg

This is not just the best-performing regression model — it is the most accurate model across the entire forecasting exercise. The substantial decline in MAD relative to the non-seasonal linear trend confirms what the data has been hinting at all along: explicit seasonal structure is absolutely critical for this dataset. Without it, even sophisticated smoothing methods cannot compete.

3.5.4 Log-Linear Trend Model with Seasonality

SUMMARY OUTPUT

Regression statistics	
Multiple R	0,902090954
R square	0,813768089
Adjusted R square	0,775890413
Standard error	0,094306045
Sample size	72

ANALYSIS OF VARIANCE

	Degrees of freedom	*SS*	*MS*	*F*	*Significance F*
Regression	12	2,292860497	0,191071708	21,48410778	3,2639E-17
Residual	59	0,524724177	0,00889363		
Total	71	2,817584675			

	Coefficients	*Standard error*	*t*	*P-value*	*Lower 95%*	*Upper 95%*	*exp(b)*
Intercept	11,97720061	0,042010752	285,0984603	2,51749E-94	11,89313729	12,06126392	159086,062
TIME	0,006067953	0,000542311	11,18905943	3,2334E-16	0,004982791	0,007153116	1,0060864
FEBRUARY	-0,046573383	0,054450321	-0,855337163	0,395824723	-0,155528224	0,062381458	0,954494514
MARCH	-0,061677055	0,054458422	-1,132553101	0,26198373	-0,170648107	0,047293996	0,940186466
APRIL	-0,170916736	0,054471922	-3,137703428	0,002656999	-0,279914801	-0,061918672	0,842891753
MAY	0,078455084	0,054490816	1,439785465	0,155213247	-0,030580786	0,187490955	1,081614773
JUNE	0,121793381	0,054515098	2,234122019	0,029277593	0,012708922	0,23087784	1,129520697
JULY	0,233743886	0,054544762	4,285359015	6,83338E-05	0,12460007	0,342887702	1,263320897
AUGUST	0,210029529	0,054579798	3,848118476	0,000294907	0,100815606	0,319243453	1,23371449
SEPTEMBER	0,129795259	0,054620197	2,376323547	0,020750647	0,020500498	0,23909002	1,138595243
OKTOBER	0,108531248	0,054665946	1,985353893	0,051759429	-0,000855057	0,217917552	1,114639738

NOVEMBER	0,093678078	0,054717031	1,712046061	0,092140275	-0,015810449	0,203166605	1,098206152
DECEMBER	0,146152553	0,054773439	2,668310679	0,009828006	0,036551154	0,255753952	1,157372735

The third specification estimates the model in logarithmic form, allowing the trend to be interpreted in relative rather than absolute terms and smoothing the evolution of the series proportionally. This model also demonstrates strong explanatory performance, with $R^2 = 0.814$ and adjusted $R^2 = 0.776$. The time coefficient remains positive and statistically significant ($\beta = 0.0061$, $p < 0.001$), while the back-transformed forecasts yield a MAD of 13,631.13.

MAD: 13,631.13

Forecast for the next period: 247,746.47 kg

Although the log-seasonal specification clearly outperforms the simple linear trend model and all smoothing-based alternatives, it falls slightly short of the linear trend model with seasonality. In this particular application, modelling monthly fixed seasonal effects in linear form appears more beneficial than imposing an additional logarithmic transformation on the data.

3.5.5 Interpretation of Regression Results

Taken together, the regression results tell a compelling story: the incorporation of seasonality produces the largest accuracy gains of any modelling decision made in this study. The linear trend model with seasonality reduces MAD by 41.6% relative to the simple linear trend model and by 34.2% relative to the best non-regression time-series method. This provides strong evidence that the demand series is not merely trending upward — it is governed by a stable monthly seasonal cycle that is far better captured through regression with seasonal dummies than through any form of smoothing alone.

3.6 Integrated Comparison of All Forecasting Methods

After estimating the moving average, weighted moving average, exponential smoothing, trend-adjusted exponential smoothing, and regression-based models, we conducted a comprehensive integrated comparison using MAD as the common evaluation criterion. Table 3.6.1 below summarizes the most relevant specifications from each methodological family and ranks them from the most accurate to the least accurate.

Rank	Method	Specification	MAD	Forecast Next Period
1	Regression	Linear trend with seasonality	12,690.21	248,425.05
2	Regression	Log-linear trend with seasonality	13,631.13	247,746.47
3	Exponential smoothing	Simple ES (α = 0.83)	19,295.92	269,661.90
4	Trend-adjusted ES	Holt-type ES (α = 0.5, β = 0.7)	19,517.49	n/a
5	Weighted moving average	Weights 0.8 / 0.2	19,529.86	269,212
6	Weighted moving average	Weights 0.9 / 0.1	19,649.13	268,817
7	Weighted moving average	Weights 0.7 / 0.3	19,733.38	269,607
8	Weighted moving average	Weights 0.6 / 0.4	20,229.89	270,002
9	Moving average	Two-period moving average	20,826.49	270,397
10	Regression	Linear trend model	21,727.90	266,941.73
11	Moving average	Three-period moving average	23,588.81	278,847.30

Table 3.6.1. Integrated ranking of the principal forecasting specifications based on MAD.

3.6.1 Cross-Method Interpretation

The integrated ranking paints a clear picture: the two regression models that explicitly incorporate seasonality dominate all smoothing-based alternatives. The linear trend model with seasonality achieved the lowest overall MAD at 12,690.21, followed by the log-linear seasonal model at 13,631.13. By contrast, the best purely time-series specification from POM-QM simple exponential smoothing with α = 0.83 produced a MAD of 19,295.92. In concrete terms, the best seasonal regression model lowers the average absolute forecasting error by approximately 34.2% relative to the best smoothing model.

Among the non-regression time-series techniques, simple exponential smoothing remained the most accurate and parsimonious option, slightly outperforming trend-adjusted exponential smoothing and the best weighted moving average. This indicates that recent observations are highly informative for the next-period forecast. Nevertheless, the much stronger performance of the seasonal regression models reveals that the dominant source of forecast improvement lies in capturing stable monthly seasonality and not in smoothing the recent history alone.

3.6.2 Final Recommendation

Based on the complete forecasting exercise, the linear trend model with seasonality is recommended as the optimal specification for this dataset. It combines the lowest MAD, strong explanatory power ($R^2 = 0.847$), and an economically interpretable structure that reflects both upward market growth and recurring monthly demand effects. The log-linear seasonal model may be retained as a robustness check, while simple exponential smoothing with α = 0.83 can serve as a useful operational benchmark when a fast-updating rule is needed. However, for strategic planning, budgeting, and medium-term demand forecasting, the seasonal linear regression model provides the strongest overall empirical foundation (Box et al., 2015; Hyndman & Athanasopoulos, 2021).

Conclusion

This thesis showed that demand forecasting in the broiler sector is not merely a statistical exercise but a strategic management tool in an environment characterized by cost pressure, perishability, narrow margins, and recurring seasonal variation. The analysis of the Greek broiler market highlighted the importance of vertical integration, contractual production arrangements, retailer bargaining power, evolving consumer preferences, and the strong influence of feed, energy, and compliance costs on business operations.

The comparative evaluation of forecasting methods demonstrated that the inclusion of seasonality is the most decisive modelling choice for this dataset. Among all examined approaches, the linear trend model with seasonality achieved the lowest Mean Absolute Deviation (MAD), outperforming both the simpler smoothing methods and the non-seasonal regression specification. This indicates that monthly broiler demand follows a pattern shaped simultaneously by a long-run upward trend and by stable intra-year fluctuations.

The practical implications of these findings are substantial. A more accurate forecasting framework can improve production scheduling, inventory management, distribution planning, and coordination across the supply chain. In a sector where forecasting errors can quickly translate into stockouts, waste, or unnecessary storage costs, the adoption of a model that captures both trend and seasonality can strengthen operational efficiency and support more informed managerial decision-making.

Finally, the thesis contributes by linking sector-specific market analysis with quantitative decision-support tools. Its results suggest that businesses operating in the Greek broiler market should not rely exclusively on simple adaptive forecasting rules when stable seasonal effects are present. Instead, forecasting models that explicitly incorporate seasonality offer a stronger empirical basis for medium-term planning and supply chain optimization.

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APPENDIX A

Linear trend model					
Residuals output					
Sample size	*Predicted quantity in kilos*	*Residuals*	*Abolute Distance*		
1	168273,7758	-35808,38576	35808,38576	***MAD=***	***21727,9***
2	169644,164	-31478,44396	31478,44396		
3	171014,5522	-41618,93216	41618,93216		
4	172384,9404	-25983,85036	25983,85036		
5	173755,3286	18495,40144	18495,40144		
6	175125,7168	26001,86324	26001,86324		
7	176496,105	49319,29504	49319,29504		
8	177866,4932	52611,72685	52611,72685		
9	179236,8814	21661,03865	21661,03865		
10	180607,2696	1665,950448	1665,950448		
11	181977,6578	6883,482248	6883,482248		
12	183348,046	26181,66405	26181,66405		
13	184718,4341	-19312,99415	19312,99415		
14	186088,8223	-16745,71235	16745,71235		
15	187459,2105	-25138,65055	25138,65055		
16	188829,5987	-80543,00875	80543,00875		
17	190199,9869	-28794,78695	28794,78695		
18	191570,3751	8054,594855	8054,594855		
19	192940,7633	27484,96666	27484,96666		
20	194311,1515	20026,99846	20026,99846		

21	195681,5397	-7043,264743	7043,264743
22	197051,9279	28384,00206	28384,00206
23	198422,3161	9111,913859	9111,913859
24	199792,7043	18781,73566	18781,73566
25	201163,0925	3812,427461	3812,427461
26	202533,4807	-1733,860738	1733,860738
27	203903,8689	-5522,998937	5522,998937
28	205274,2571	-12433,80714	12433,80714
29	206644,6453	23082,30466	23082,30466
30	208015,0335	24235,75647	24235,75647
31	209385,4217	60992,01827	60992,01827
32	210755,8099	49635,88007	49635,88007
33	212126,1981	12678,61187	12678,61187
34	213496,5863	-12608,94633	12608,94633
35	214866,9745	-15372,69453	15372,69453
36	216237,3627	-7289,62273	7289,62273
37	217607,7509	-13615,54093	13615,54093
38	218978,1391	-42072,68913	42072,68913
39	220348,5273	-24959,98733	24959,98733
40	221718,9155	-58961,46553	58961,46553
41	223089,3037	1846,936275	1846,936275
42	224459,6919	-7998,871924	7998,871924
43	225830,0801	28289,89988	28289,89988
44	227200,4683	21038,90168	21038,90168
45	228570,8565	22313,49348	22313,49348
46	229941,2447	6056,695279	6056,695279
47	231311,6329	12803,00708	12803,00708
48	232682,0211	37772,80888	37772,80888
49	234052,4093	3410,170682	3410,170682
50	235422,7975	-34091,22502	34091,22502
51	236793,1857	-22955,14572	22955,14572

52	238163,5739	-60526,32392	60526,32392
53	239533,9621	4762,398485	4762,398485
54	240904,3503	-6921,080314	6921,080314
55	242274,7385	7787,657487	7787,657487
56	243645,1267	5379,453888	5379,453888
57	245015,5149	7024,951089	7024,951089
58	246385,9031	-14893,44811	14893,44811
59	247756,2913	-4392,801309	4392,801309
60	249126,6795	9651,490491	9651,490491
61	250497,0677	-20145,25771	20145,25771
62	251867,4559	-16999,87591	16999,87591
63	253237,8441	-39399,80411	39399,80411
64	254608,2323	-27815,88231	27815,88231
65	255978,6205	-19025,1605	19025,1605
66	257349,0087	6995,517297	6995,517297
67	258719,3969	37649,9031	37649,9031
68	260089,7851	26628,1949	26628,1949
69	261460,1733	9752,176699	9752,176699
70	262830,5615	32917,9085	32917,9085
71	264200,9497	8171,080301	8171,080301
72	265571,3379	2850,242102	2850,242102

APPENDIX B

Linear trend model with seasonality

Residuals output

Sample size	*Predicted quantity in kilos*	*Residuals*	*Absolut residuals*		
1	158168,666	-25703,27597	25703,28	***MAD=***	***12690,21159***
2	149295,3497	-11129,62972	11129,63		
3	147920,1193	-18524,4993	18524,5		
4	131512,371	14888,71903	14888,72		
5	177321,3311	14929,39893	14929,4		
6	187025,167	14102,41303	14102,41		
7	215254,882	10560,51803	10560,52		
8	210591,5061	19886,71393	19886,71		
9	193806,2028	7091,717197	7091,717		
10	191032,4501	-8759,230136	8759,23		
11	188349,8093	511,330697	511,3307		
12	201510,9193	8018,790697	8018,791		
13	173211,3962	-7805,956248	7805,956		
14	164338,08	5005,030002	5005,03		
15	162962,8496	-642,2895818	642,2896		
16	146555,1012	-38268,51125	38268,51		

17	192364,0613	-30958,86135	30958,86
18	202067,8972	-2442,927248	2442,927
19	230297,6122	-9871,882248	9871,882
20	225634,2363	-11296,08635	11296,09
21	208848,9331	-20210,65808	20210,66
22	206075,1804	19360,74958	19360,75
23	203392,5396	4141,690418	4141,69
24	216553,6496	2020,790418	2020,79
25	188254,1265	16721,39347	16721,39
26	179380,8103	21418,80972	21418,81
27	178005,5799	20375,29014	20375,29
28	161597,8315	31242,61847	31242,62
29	207406,7916	22320,15837	22320,16
30	217110,6275	15140,16247	15140,16
31	245340,3425	25037,09747	25037,1
32	240676,9666	19714,72337	19714,72
33	223891,6634	913,1466394	913,1466
34	221117,9107	-20230,27069	20230,27
35	218435,2699	-18940,98986	18940,99
36	231596,3799	-22648,63986	22648,64
37	203296,8568	695,3531939	695,3532
38	194423,5406	-17518,09056	17518,09
39	193048,3101	2340,229861	2340,23
40	176640,5618	-13883,11181	13883,11
41	222449,5219	2486,718094	2486,718
42	232153,3578	-15692,53781	15692,54
43	260383,0728	-6263,092806	6263,093
44	255719,6969	-7480,326906	7480,327
45	238934,3936	11949,95636	11949,96
46	236160,641	-162,7009727	162,701
47	233478,0001	10636,63986	10636,64

48	246639,1101	23815,71986	23815,72
49	218339,5871	19122,99292	19122,99
50	209466,2708	-8134,698335	8134,698
51	208091,0404	5746,999582	5747
52	191683,2921	-14046,04208	14046,04
53	237492,2522	6804,108415	6804,108
54	247196,0881	-13212,81808	13212,82
55	275425,8031	-25363,40708	25363,41
56	270762,4272	-21737,84658	21737,85
57	253977,1239	-1936,657918	1936,658
58	251203,3713	-19710,91625	19710,92
59	248520,7304	-5157,240418	5157,24
60	261681,8404	-2903,670418	2903,67
61	233382,3174	-3030,507364	3030,507
62	224509,0011	10358,57889	10358,58
63	223133,7707	-9295,730697	9295,731
64	206726,0224	20066,32764	20066,33
65	252534,9825	-15581,52246	15581,52
66	262238,8184	2105,707636	2105,708
67	290468,5334	5900,766636	5900,767
68	285805,1575	912,8225363	912,8225
69	269019,8542	2192,495803	2192,496
70	266246,1015	29502,36847	29502,37
71	263563,4607	8808,569303	8808,569
72	276724,5707	-8302,990697	8302,991

APPENDIX C

Log-Linear Trend Model **with Seasonality**

Residuals output

Sample size	*Predicted lnq*	*Residuals*	*Standardized residuals*	*Y*	*real data*	*absolute (prediction data-real data)*	MAD
1	11,98326856	-0,189191875	-2,200726734	160054,3235	132465	27589	13631,1286
2	11,94276313	-0,106554015	-1,239462681	153700,799	138166	15535	
3	11,93372741	-0,163097597	-1,89719163	152318,2574	129396	22923	
4	11,83055568	0,063549645	0,739225199	137386,8133	146401	9014	
5	12,08599546	0,080560229	0,937096531	177370,3955	192251	14880	
6	12,1354017	0,076293007	0,887459148	186353,6898	201128	14774	
7	12,25342016	0,074052967	0,861402445	209697,2627	225815	16118	
8	12,23577376	0,112137887	1,304415668	206029,3183	230478	24449	
9	12,16160744	0,048944755	0,569337504	191301,7767	200898	9596	
10	12,14641138	-0,033149335	-0,385601273	188416,7199	182273	6143	
11	12,13762617	0,011141147	0,129596583	186768,688	188861	2092	
12	12,1961686	0,056452226	0,65666627	198028,9668	209530	11501	
13	12,056084	-0,039929045	-0,464464537	172143,5492	165405	6738	
14	12,01557857	0,024103607	0,280379119	165310,1302	169343	4033	
15	12,00654285	-0,009214423	-0,107184445	163823,1624	162321	1503	
16	11,90337112	-0,310834516	-3,615704048	147763,9163	108287	39477	
17	12,15881089	-0,167137641	-1,944186414	190767,5391	161405	29362	

18	12,20821714	-0,004021407	-0,046778006	200429,3596	199625	804
19	12,3262356	-0,022919509	-0,266605408	225536,1197	220426	5110
20	12,3085892	-0,03327901	-0,387109684	221591,128	214338	7253
21	12,23442288	-0,086836309	-1,010101445	205751,1855	188638	17113
22	12,21922682	0,106564451	1,23958408	202648,2147	225436	22788
23	12,21044161	0,032609963	0,379327167	200875,7036	207534	6659
24	12,26898403	0,025897888	0,301250647	212986,4939	218574	5588
25	12,12889943	0,101746403	1,183539344	185145,8985	204976	19830
26	12,088394	0,121668771	1,415281262	177796,3376	200800	23003
27	12,07935828	0,118585763	1,379418953	176197,0561	198381	22184
28	11,97618656	0,193431885	2,250047578	158924,8228	192840	33916
29	12,23162633	0,113020378	1,314681016	205176,5959	229727	24550
30	12,28103258	0,074540478	0,867073292	215568,1932	232251	16683
31	12,39905104	0,108523149	1,262368134	242571,3175	270377	27806
32	12,38140463	0,088537641	1,029891765	238328,3527	260392	22063
33	12,30723832	0,015749475	0,183201797	221291,9873	224805	3513
34	12,29204226	-0,081541234	-0,948507822	217954,6429	200888	17067
35	12,28325704	-0,0797162	-0,927278575	216048,2504	199494	16554
36	12,34179947	-0,09196002	-1,069701716	229073,7932	208948	20126
37	12,20171487	0,024122214	0,280595568	199130,3415	203992	4862
38	12,16120944	-0,077838753	-0,90543965	191225,6535	176905	14320
39	12,15217372	0,030571645	0,355616947	189505,575	195389	5883
40	12,04900199	-0,04898566	-0,569813322	170928,7351	162757	8171
41	12,30444177	0,019130495	0,22253065	220673,9979	224936	4262
42	12,35384802	-0,068683178	-0,798939731	231850,4935	216461	15390
43	12,47186648	-0,02630468	-0,30598255	260893,2181	254120	6773
44	12,45422007	-0,032071311	-0,373061435	256329,7736	248239	8090
45	12,38005376	0,052693599	0,612944989	238006,6173	250884	12878
46	12,3648577	0,006720658	0,078176353	234417,1964	235998	1581
47	12,35607248	0,049320749	0,573711161	232366,8103	244115	11748
48	12,41461491	0,093245467	1,084654356	246376,1986	270455	24079

49	12,27453031	0,103235023	1,200855343	214171,0576	237463	23292
50	12,23402488	-0,021316437	-0,247958071	205669,3126	201332	4338
51	12,22498916	0,047985025	0,558173687	203819,3131	213838	10019
52	12,12181743	-0,034318604	-0,399202495	183839,327	177637	6202
53	12,37725721	0,028880153	0,335941095	237341,9498	244296	6954
54	12,42666346	-0,06365856	-0,740492129	249362,6286	233983	15379
55	12,54468191	-0,115216165	-1,340222953	280599,0089	250062	30537
56	12,52703551	-0,101728623	-1,183332523	275690,8782	249025	26666
57	12,45286919	-0,015524261	-0,180582045	255983,7369	252040	3943
58	12,43767314	-0,085370575	-0,993051666	252123,1999	231492	20631
59	12,42888792	-0,026576471	-0,309144086	249917,944	243363	6554
60	12,48743035	-0,02370386	-0,275729167	264985,4896	258778	6207
61	12,34734575	1,72808E-05	0,000201015	230347,8294	230352	4
62	12,30684032	0,059936828	0,697200021	221203,9304	234868	13664
63	12,2978046	-0,024830413	-0,288833513	219214,1968	213838	5376
64	12,19463287	0,13715725	1,595447088	197725,082	226792	29067
65	12,45007264	-0,074453615	-0,866062878	255268,8657	236953	18315
66	12,49947889	-0,01447034	-0,168322573	268197,4907	264345	3853
67	12,61749735	-0,018135761	-0,210959667	301793,2177	296369	5424
68	12,59985095	-0,033596585	-0,390803791	296514,366	286718	9796
69	12,52568463	-0,015027259	-0,174800799	275318,7046	271212	4106
70	12,51048857	0,086776035	1,009400327	271166,5734	295748	24582
71	12,50170336	0,013220811	0,153787751	268794,7501	272372	3577
72	12,56024578	-0,059931702	-0,697140391	285000,3778	268422	16579

APPENDIX D

Year	Month	quantities in kilos	time	FEBRUARY	MARCH	APRIL	MAY	JUNE	JULY	AUGUST	SEPTEMBER	OKTOBER	NOVEMBER	DECEMBER	lnq
2019	1	132465	1	0	0	0	0	0	0	0	0	0	0	0	11,79408
2019	2	138166	2	1	0	0	0	0	0	0	0	0	0	0	11,83621
2019	3	129396	3	0	1	0	0	0	0	0	0	0	0	0	11,77063
2019	4	146401	4	0	0	1	0	0	0	0	0	0	0	0	11,89411
2019	5	192251	5	0	0	0	1	0	0	0	0	0	0	0	12,16656
2019	6	201128	6	0	0	0	0	1	0	0	0	0	0	0	12,21169
2019	7	225815	7	0	0	0	0	0	1	0	0	0	0	0	12,32747
2019	8	230478	8	0	0	0	0	0	0	1	0	0	0	0	12,34791
2019	9	200898	9	0	0	0	0	0	0	0	1	0	0	0	12,21055
2019	10	182273	10	0	0	0	0	0	0	0	0	1	0	0	12,11326
2019	11	188861	11	0	0	0	0	0	0	0	0	0	1	0	12,14877
2019	12	209530	12	0	0	0	0	0	0	0	0	0	0	1	12,25262
2020	1	165405	13	0	0	0	0	0	0	0	0	0	0	0	12,01615
2020	2	169343	14	1	0	0	0	0	0	0	0	0	0	0	12,03968
2020	3	162321	15	0	1	0	0	0	0	0	0	0	0	0	11,99733

2020	4	108287	16	0	0	1	0	0	0	0	0	0	0	0	11,59254
2020	5	161405	17	0	0	0	1	0	0	0	0	0	0	0	11,99167
2020	6	199625	18	0	0	0	0	1	0	0	0	0	0	0	12,2042
2020	7	220426	19	0	0	0	0	0	1	0	0	0	0	0	12,30332
2020	8	214338	20	0	0	0	0	0	0	1	0	0	0	0	12,27531
2020	9	188638	21	0	0	0	0	0	0	0	1	0	0	0	12,14759
2020	10	225436	22	0	0	0	0	0	0	0	0	1	0	0	12,32579
2020	11	207534	23	0	0	0	0	0	0	0	0	0	1	0	12,24305
2020	12	218574	24	0	0	0	0	0	0	0	0	0	0	1	12,29488
2021	1	204976	25	0	0	0	0	0	0	0	0	0	0	0	12,23065
2021	2	200800	26	1	0	0	0	0	0	0	0	0	0	0	12,21006
2021	3	198381	27	0	1	0	0	0	0	0	0	0	0	0	12,19794
2021	4	192840	28	0	0	1	0	0	0	0	0	0	0	0	12,16962
2021	5	229727	29	0	0	0	1	0	0	0	0	0	0	0	12,34465
2021	6	232251	30	0	0	0	0	1	0	0	0	0	0	0	12,35557
2021	7	270377	31	0	0	0	0	0	1	0	0	0	0	0	12,50757
2021	8	260392	32	0	0	0	0	0	0	1	0	0	0	0	12,46994
2021	9	224805	33	0	0	0	0	0	0	0	1	0	0	0	12,32299
2021	10	200888	34	0	0	0	0	0	0	0	0	1	0	0	12,2105

2021	11	199494	35	0	0	0	0	0	0	0	0	0	1	0	12,20354
2021	12	208948	36	0	0	0	0	0	0	0	0	0	0	1	12,24984
2022	1	203992	37	0	0	0	0	0	0	0	0	0	0	0	12,22584
2022	2	176905	38	1	0	0	0	0	0	0	0	0	0	0	12,08337
2022	3	195389	39	0	1	0	0	0	0	0	0	0	0	0	12,18275
2022	4	162757	40	0	0	1	0	0	0	0	0	0	0	0	12,00002
2022	5	224936	41	0	0	0	1	0	0	0	0	0	0	0	12,32357
2022	6	216461	42	0	0	0	0	1	0	0	0	0	0	0	12,28516
2022	7	254120	43	0	0	0	0	0	1	0	0	0	0	0	12,44556
2022	8	248239	44	0	0	0	0	0	0	1	0	0	0	0	12,42215
2022	9	250884	45	0	0	0	0	0	0	0	1	0	0	0	12,43275
2022	10	235998	46	0	0	0	0	0	0	0	0	1	0	0	12,37158
2022	11	244115	47	0	0	0	0	0	0	0	0	0	1	0	12,40539
2022	12	270455	48	0	0	0	0	0	0	0	0	0	0	1	12,50786
2023	1	237463	49	0	0	0	0	0	0	0	0	0	0	0	12,37777
2023	2	201332	50	1	0	0	0	0	0	0	0	0	0	0	12,21271
2023	3	213838	51	0	1	0	0	0	0	0	0	0	0	0	12,27297
2023	4	177637	52	0	0	1	0	0	0	0	0	0	0	0	12,0875
2023	5	244296	53	0	0	0	1	0	0	0	0	0	0	0	12,40614

2023	6	233983	54	0	0	0	0	1	0	0	0	0	0	0	12,363
2023	7	250062	55	0	0	0	0	0	1	0	0	0	0	0	12,42947
2023	8	249025	56	0	0	0	0	0	0	1	0	0	0	0	12,42531
2023	9	252040	57	0	0	0	0	0	0	0	1	0	0	0	12,43734
2023	10	231492	58	0	0	0	0	0	0	0	0	1	0	0	12,3523
2023	11	243363	59	0	0	0	0	0	0	0	0	0	1	0	12,40231
2023	12	258778	60	0	0	0	0	0	0	0	0	0	0	1	12,46373
2024	1	230352	61	0	0	0	0	0	0	0	0	0	0	0	12,34736
2024	2	234868	62	1	0	0	0	0	0	0	0	0	0	0	12,36678
2024	3	213838	63	0	1	0	0	0	0	0	0	0	0	0	12,27297
2024	4	226792	64	0	0	1	0	0	0	0	0	0	0	0	12,33179
2024	5	236953	65	0	0	0	1	0	0	0	0	0	0	0	12,37562
2024	6	264345	66	0	0	0	0	1	0	0	0	0	0	0	12,48501
2024	7	296369	67	0	0	0	0	0	1	0	0	0	0	0	12,59936
2024	8	286718	68	0	0	0	0	0	0	1	0	0	0	0	12,56625
2024	9	271212	69	0	0	0	0	0	0	0	1	0	0	0	12,51066
2024	10	295748	70	0	0	0	0	0	0	0	0	1	0	0	12,59726
2024	11	272372	71	0	0	0	0	0	0	0	0	0	1	0	12,51492
2024	12	268422	72	0	0	0	0	0	0	0	0	0	0	1	12,50031