

NONLINEAR SURGE PRICING

Technical Field

The present invention relates, in general terms, to systems and methods for dynamically pricing use of services based on supply and demand interactions. More specifically, the invention relates to, but is not limited to, pricing uses of a service such as a ride hailing service based on demand surges.

Background

Nonlinear surge (NLS) is a feature that is generally designed increase prices when demand increases, or where demand exceeds supply. The intention is to maintain the rate at which services are used while increasing the profit resulting from uses of those services. In a ride-hailing context, NLS is used to maintain BTR (Book Through Rate) for long distance trips.

NLS tends to remain fixed after launch or is only very infrequently updated.

Surrogate updated surge pricing models can be produced from historical data to replace the coefficients and functions used for existing levels of service. However, surrogate models are difficult to extend to new markets such as new cities, since there is no historical data with optimized NLS functions that can be leveraged into the surrogate, and such historical data may not capture service parameters that are now of importance – e.g. where a city only captured the provision of services and did not capture the level of service provided, such as standard vehicle, large vehicle and luxury vehicle levels of service.

It would be desirable to overcome or partially address at least one of the above-described problems, or at least to provide a useful alternative.

Summary

Disclosed herein is a constrained nonlinear optimization framework that enables non-linear surge (NLS) to shape demand more effectively than previous models. Demand may be shaped based on an optimised function, to meet the various business objectives with well-defined constraints – for example, to optimize profitability beyond just maintaining the book-through-rate (BTR) of long-distance trips. The proposed methods are automated, intelligent approaches to adjusting pricing for services depending on the parameters of the service. The context used herein is that of ride-hailing, where the service is a trip or ride and the surge pricing relates to fares for trips based on parameters for the trip – e.g. distance.

Disclosed herein is a system for determining nonlinear surge pricing, comprising:

- memory; and

- a processing system comprising one or more processors, the memory storing instructions that, when executed by the processing system, cause the system to:

 - obtain historical data relating to uses of a service by one or more users, and provision of the service by one or more providers;

 - determine a user pricing elasticity model and a provider pricing elasticity model from the data relating to the uses of the service and provision of the service;

 - obtain an original nonlinear surge pricing model and service parameters;

 - optimise an objective function based on a weighted combination of a predicted number of uses of the service and a predicted gross merchandise value (predicted GMV), the original nonlinear surge pricing model, the service parameters and one or both of the user pricing elasticity model and the provider pricing elasticity model;

 - output an augmented surge multiplier for a new request for use of the service, based on the optimised objective function and a surge

multiplier determined from the original surge pricing.

The data relating to the uses of the service and provision of the service may comprise service parameters for a plurality of requested uses of the service. The system may then determine the user pricing elasticity model and the provider pricing elasticity model by:

- applying coefficients to the service parameters to produce modified service parameters; and

- using linear regression on the modified service parameters.

A sign of coefficients can be constrained in this regression analysis, to maintain causality between, for each requested use of the service, the service parameters and usage of the service.

The requested uses of the service can comprise cancelled uses.

The system may identify a level of service (e.g. standard, premium and so on) in the new request for use of the service and outputs the augmented surge multiplier based on the level of service.

The system may receive one or more limits each limit defining a minimum or maximum surge multiplier, and the objective function is optimised within the limit or limits. The one or more limits can include a minimum ratio, and a maximum ratio, between a surge price determined from the original nonlinear surge pricing model and a surge price determined from the augmented surge multiplier.

The system may be configured to determine the weighted combination by applying a number between "0" and "1" for each of the predicted number of uses and the predicted GMV. Such cases may involve applying a "0" for one of the predicted number of uses and the predicted GMV, and a "1" for the other of the predicted number of uses and the predicted GMV.

The service parameters may comprise a level of service and the system

optimises the objective function separately for each level of service. Where the historical data relates to a plurality of requested uses of the service, each request comprising a level of service, the system may determine a separate user pricing elasticity model and provider pricing elasticity model for each level of service. Thus, outputting the augmented surge multiplier can comprise outputting a separate augmented surge multiplier for each level of service.

Also disclosed is a method for determining nonlinear surge pricing, comprising:

- obtaining historical data relating to uses of a service by one or more users, and provision of the service by one or more providers;

- determining a user pricing elasticity model and a provider pricing elasticity model from the data relating to the uses of the service and provision of the service;

- obtaining an original nonlinear surge pricing model and service parameters;

- optimising an objective function based on a weighted combination of a predicted number of uses of the service and a predicted gross merchandise value (predicted GMV), the original nonlinear surge pricing model, the service parameters and one or both of the user pricing elasticity model and the provider pricing elasticity model;

- outputting an augmented surge multiplier for a new request for use of the service, based on the optimised objective function and a surge multiplier determined from the original surge pricing.

The data relating to the uses of the service and provision of the service may comprise service parameters for a plurality of requested uses of the service, the method comprising determining the user pricing elasticity model and the provider pricing elasticity model by:

- applying coefficients to the service parameters to produce modified service parameters; and

- using linear regression on the modified service parameters, wherein a sign of coefficients is constrained to maintain causality between, for each requested use of the service, the service parameters and usage of the

service.

To summarize, NLS is upgraded by the present teachings, to make NLS extendable to new cities, as well as optimizable based on latest market conditions and other objectives.

Advantageously, the methods described herein optimise surge pricing using a non-linear model based on user and provider behaviours that can be augmented with current surge pricing models to maintain relevance to new geographies or markets.

Brief description of the drawings

Embodiments of the present invention will now be described, by way of non-limiting example, with reference to the drawings in which:

Figure 1 is a method for determining nonlinear surge pricing;

Figure 2 illustrates the surge phenomenon in the context of ride hailing;

Figure 3 shows passenger surge behaviour based on distance; and

Figure 4 is a system for determining nonlinear surge pricing.

Detailed description

The non-linear surge pricing methodologies presented herein extends original surge pricing models based on current surge pricing schemes and recently captured data. In embodiments, methods for determining non-linear surge pricing can leverage recent historical data – e.g. the last month's worth of service usage data – and current surge pricing models, to provide an enhanced, objective based, surge pricing multiplier to properly price services based on demand.

The discussion below will be made with reference to trips or rides using a ride hailing service. However, the same teachings are applicable to other services where there are demand peaks, such as hotel bookings during peak season, document delivery services in peak (mid-afternoon) versus other times of day, food delivery around meal times when compared with other times of day, and so on. The skilled person will appreciate that the methodologies described herein are intended to be extended to other industries and services without departing from the teachings given herein.

Figure 1 illustrates the broad features of the present methodology, in the form of a method 100 for determining NLS pricing. Surge pricing is the price of using a particular service based on demand surges. The NLS pricing produced by method 100 is a dynamic pricing tool for determining the surge pricing for transportation fares (or other services), based on factors such as distance, passengers' response and drivers' response to price changes. There are also user-configured parameters for instance, the main objectives that they seek to achieve such as the rides or GMV conversion, and the different weights and coefficients. Specifically:

- The objective function used is a multi-objective function where there are coefficients on both the simulated rides and simulated GMV that result in a convex combination: $a \cdot \text{simulated_rides} + b \cdot \text{simulated_GMV}$ where a and b are the user-configured parameters and $a+b = 1$.
- An example of the constraints used is the upper bound on the NLS: $\text{NLS} < c \cdot \text{original surge}$ and c is the user-configured parameter here.

NLS uses these factors and user-configured parameters (e.g. level of service) as inputs and gives the surge multiplier as output to modify the transport fares.

Figure 2 illustrates the surge phenomenon in the context of ride hailing. Surge is clustered into buckets based on distance. There are multiple measures for distance, such as physical distance and effective distance, where physical distance is the distance a passenger will travel between the origin and destination, and the effective distance which is defined as $\text{NSNS fare} / \text{min fare}$

per km, where NSNS fare is the No-surcharge and no-surge fare. Figure 2 makes it clear that in the absence of surge the Book-through Rate (BTR), defined as number of bookings/number of unique check-price sessions (such a session being when a user checks the price of a ride), decreases as distance increases. This is expected since the price increases with distance. When surge is moderate ($1.1x \sim 1.6x$ of NSNS fare), BTR flattens across distance buckets. When surge is high (>1.6), BTR remains flat over the lower distances ($5 \sim 10$ km), and then increases with further increased distance. One possible reason for this shape in the curve is that when surge is high, or during peak hours, long distance trips have lower price elasticity. This observation may be explained by the correlation of higher surge during periods with higher demand such as peak hours where passengers are more willing to pay when they are in a rush. If the objective function described with reference to step 108 is designed to optimise revenue, resolving surge pricing during high surge periods may help capture additional revenue lost by the NLS model in relation to which the data for Figure 2 was captured.

One confounding factor in determining surge is that drivers are often less inclined to take jobs when the fares are very low. This increases demand for periods that would otherwise not experience surge. In fact, many drivers turn off their apps altogether to avoid automatically receiving jobs and then having to cancel, which would otherwise impact their approval rating.

For these reasons, it is difficult to estimate or learn the BTR that would result if alternative surge pricing models were developed from scratch. Data are solely derived from observed BTR for our actual surge distributions, whereas BTR response for different surge distributions is not able to be accurately predicted. To assist in predicting BTR, a base BTR can be inferred by filtering data based on a surge of 1.0 – i.e. no surge in demand. A new NLS pricing model can also leverage BTR trends across times – e.g. peak vs non-peak, weekdays vs weekends, origin and destination combinations, and geographical areas.

To address the unknowable response of new surge pricing models when

developing new surge pricing models, the method 100 models the user and provider behaviours, and consumes the current surge pricing model, when optimising an objective function to produce a new, augmented surge pricing model from which augmented surge pricing can be calculated. To that end, the method 100 comprises the steps of:

102: obtaining data;

104: determining user (passenger) and provider (driver) pricing elasticity models from the data obtained at step 102;

106: obtaining the original NLS model and service parameters;

108: optimising an objective function over the elasticity models, original NLS model and service parameters, to meet a predefined objective; and

110: outputting an augmented surge multiplier based on the objective function and surge multiplier from the original NLS model.

Step 102 will generally involve extracting historical data from a database. The data may be obtained through various other means but it is anticipated that many service providers will house their own historical data in database. The historical data relates to uses of the service in question by one or more passengers, and provision of the service by one or more providers. In general, the data will be derived from a large number of passengers and drivers. To that end, the historical data can be used to model passenger and driver behaviour.

The historical data are taken to include any necessary information enabling the method 100, in its various embodiments, to be performed. For example, the services parameters can include the distance of a ride, price at which the ride was sold or attempted to be sold (where the historical data includes rejected rides, where the passenger opted not to book the ride), the level of service (e.g. where a standard service, premium service, large car and other service types are offered – a "level" of service and a "type" of service will be used interchangeably, without loss of generality of the term "type").

Step 104 involves determining a user pricing elasticity model (PAX model) and

a provider pricing elasticity model (DAX model for driver behaviour) from the data obtained at step 102. The PAX and DAX models model passengers' responses and drivers' responses to price changes.

The models are nonlinear to ensure that the surge is adapted to enable the objective function to optimise across distances and surge levels. This avoids the circumstance where a single surge pricing value is applied to all requests made within a geohash-minute bucket – i.e. a distance bucket for ride requests made in a particular geographical region. Otherwise, drivers may reject shorter trips (rides) in lieu of longer, higher earning trips, and passengers may not choose longer distance trips due to the expense.

So, the PAX and DAX models are based on machine learning techniques for modelling the price elasticity (how demand responds to change in the price of the service) behaviour of both passengers and drivers. This approach imbues the augmented NLS model with a more accurate understanding of the real market, empowering it to determine optimal surge values.

Regarding the PAX model, a passenger's BTR is a proxy for price elasticity of demand. Data shows that PAX model trends are different for different distances though, in general, a 'U' shaped behaviour is exhibited that has narrower valleys as distances increases, as shown in Figure 3. A possible reason for the narrower valleys is that long distance trips in in some geographical region are more price inelastic during peak hours (when surge is high), thus a higher surge pricing multiplier may be applied without significant loss of service utilisation.

Relevantly, the data obtained at step 102 will generally include service parameters for a plurality of requested uses of the service. The service parameters can include parameters such as distance, price, service level (type), driver rating (where drivers are given a rating based on the passengers' experience), time of day, weather, origin, destination and other parameters. Step 104 will therefore involve applying coefficients to the service parameters to produce modified service parameters, and using linear regression on the

modified service parameters to develop the PAX model (e.g. the PAX and DAX models may be functions determined by regression over the service parameters and other terms mentioned here). The terms that are regressed on include the aforementioned service parameters, as well as interaction terms and nonlinear combinations of the service parameters (hence the term 'modified' service parameters). The determination of these interaction and nonlinear combinations can be from contextual knowledge and causal reasoning.

The coefficients are intended to weight the service parameters. These coefficients may be learned by a machine learning model, that maps the service parameters to use or rejection of the ride. The sign of the coefficients will typically be constrained to maintain causality between the ride parameters and usage of the ride, for each requested ride. Notably, not all requests will end with the passenger accepting the ride – i.e. using the service. Thus, the data includes cancelled or rejected uses, being requests that the passenger rejects once a price for fulfilment of the request is displayed.

The PAX model also accommodates different markets in the same geographical region. For example, some people will only book a standard service, others will only book a premium service and some will book a mix of services. The PAX model may therefore be separately developed for each ride type, since the price elasticity behaviours of different market segments can differ significantly. This similarly enables an augmented surge multiplier to be produced that depends on the type of service the passenger requests.

The DAX model (provider or driver elasticity model) similarly models driver response to surge. It has been observed that there is often fewer drivers available when fares are low, since do not wish to accept the low fares (prices). This explains why there is an increase in BTR is observed when fares increase, but only to an extent.

The PAX and DAX models can be formulated as any appropriate type of model. In some embodiments, the PAX and DAX models are determined based on linear

regression or curving fitting on features such as the original surge, distance and their transformations and interaction terms. For example, these terms include distance*surge, and $e^{(-\text{distance})}$, where the determination of these interaction and nonlinear combinations can be from contextual knowledge and causal reasoning. The regression models may be produced separately for each of a plurality of service levels – ride types, such as standard premium, extra large, pet mobility impaired and others.

The same service parameters and considerations can be taken into account when learning the DAX model.

The augmented NLS model learned using the method 100 leverages the original NLS pricing model underpinning the DAX and PAX models. To that end, step 106 involves obtaining the original NLS pricing model and service parameters. Some of the service parameters are user configured, such as the level of service, and others are automatically determined, such as the distance from origin to destination, the maximum wait time and others.

The original NLS model will have been developed with particular objectives in mind. Those objectives may differ from the objective or objectives of the optimisation model learned at step 108. For example, the original NLS model may be directed to maintaining BTR across distances for a given surge level, by decreasing the surge for longer distance trips. In contrast, the augmented NLS multiplier may be produced by an objective function developed to maximise GMV, to maximise the ride network efficiency or throughput – e.g. allocate drivers to geographical locations depending on demand exhibited or forecast for those locations – to reduce passenger wait times.

Step 108 involves optimising an objective function: a convex combination of the simulated rides and gmV, $a*\text{simulated_rides} + b*\text{simulated_GMV}$, where a and b are the *user-configured* parameters and $a+b = 1$. For instance, if the user objective is simply to maximise GMV due to the overall business goal, then $a =$

0 and $b = 1$. Optimisation is intended to achieve a desired goal such as maximising predicted gross merchandise value (GMV).

- To maximise GMV, for each predetermined area and time (e.g. geohash minute) bucket, a safeguard is implemented on the number of rides, which is written into the constraint of the optimisation problem where: the number of rides after new NLS can deviate by at most a predetermined tolerance $\{bookings_tolerance\}$ from the number of rides with the current final surge.
- If the objective is instead to maximise the number of rides, a safeguard is again implemented on the GMV, where the total GMV after augmented NLS can deviate by at most $\{gmv_tolerance\}$ from the GMV with the current final surge.

Hence, optimisation may not be based on a single objective but may instead be based on multiple objectives – e.g. a weighted combination of a predicted number of uses of the service and a predicted gross merchandise value (predicted GMV). Moreover, other objectives can be added to the optimisation model, or used to replace the predicted number of rides and predicted GMV. For example, the objective function may be set to maximise the effective acceptance rate of the drivers (EAR) which is defined as the number of accepted bookings over the number of bookings broadcasted to the drivers. Further options may be set to allow for a more flexible multi-objective approach such as maximising average EAR and average GMV, using the function:

$$\max(c_1 \text{AverageEAR} + c_2 \text{averageGMV})$$

In optimising the objective function, the original nonlinear surge pricing model, the service parameters and one or both of the user pricing elasticity model and the provider pricing elasticity model are consumed. To ensure there is not a mismatch between the augmented NLS multiplier for the passenger and the driver, step 108 will generally consume both the DAX and PAX models. This will avoid a NLS multiplier being produced that is acceptable to a passenger but not to a driver (e.g. too low), or acceptable to a driver but not to a passenger (e.g. too high).

The objective function may apply a weighted combination of its inputs and/or endeavour to achieve a weighted combination of its goals. For example, if the objective function has multiple objectives – e.g. maximising predicted GMV and maximising predicted number of uses – the weighted combination of those objectives will involve applying a number between "0" and "1" for each of the predicted number of uses and the predicted GMV. To use the same framework to limit the objective function to achieving a single objective the weighted combination can include a "0" for one of the predicted number of uses and the predicted GMV, and a "1" for the other of the predicted number of uses and the predicted GMV. In weighting the inputs, a high weight may be placed on the ride type or distance, when compared with wait time or other parameters.

Where the objective function is intended to maximise revenue or GMV, the formula for GMV may be given by:

$$GMV = \sum_{bucket} BTR_{bucket}(NLS_{bucket}) * finalfare_{bucket}(NLS_{bucket}) * FC_{bucket} * FR_{bucket}$$

where a bucket could be distance-hour level, assuming no bookings cancellations. In this case, the architecture used to learn or optimise the objective function may seek to manage the trade-off between increasing the BTR for longer trips while not decreasing the EAR for longer trips too much.

After producing the optimisation model and completing the optimisation process, optimised coefficients of the NLS function are obtained. The NLS function takes into account a ride-level distance and original surge pricing contained in a new request for use of the service (ride hailing service), and determines the augmented surge multiplier. The augmented surge multiplier is outputted at step 110.

The optimisation model can further be constrained to ensure it produces sensible results – e.g. results that do not overly deprive the drivers of adequate

fares and do not shock the market when compared with pricing determined by the original NLS model. To that end, the method 100 may comprise receiving one or more limits at step 114. The limits may in fact be received at any time at the time of, or in advance of, optimising the objective function. Each limit defines a minimum or maximum surge multiplier, and the objective function is optimised within the limit or limits.

The limits can include a lower surge ratio (e.g. 0.5 for Singapore vehicles) and upper surge ratio (e.g. 1.02 for Singapore vehicles), being the minimum ratio and the maximum ratio of the proposed NLS to the original surge, respectively – augmented NLS price may therefore be within the range $[\{lower_surge_ratio\}, \{upper_surge_ratio\}] * original_surge$. The limits can further include a lower surge NLS ratio (e.g 0.5 for Singapore vehicles) and upper surge nls ratio (e.g 1.1 for Singapore vehicles), being the minimum and the maximum ratio of the proposed NLS to the current NLS, respectively – augmented NLS price may therefore be within the range $[\{lower_surge_nls_ratio\}, \{upper_surge_nls_ratio\}] * current_nls$. A further limit may be a NLS gap cap (NA for TT 199) being the maximum gap between the proposed NLS to the current NLS – this is to avoid shocking the market for the service. Yet a further limit may be the bookings tolerance or GMV tolerance (e.g. 20% for TT 199), being the maximum allowable change in bookings or GMV. Using these limits, the objective function may maximise a weighted combination of the number of rides and GMV.

The optimisation model and process outputs the coefficients of the NLS function. Thus, step 108 outputs the NLS function, or coefficients of the NLS function optimized based on the objective or objectives. For any subsequent ride request, at step 110 the NLS function consumes the distance, between the origin and destination of the ride, and the current surge and outputs the augmented surge multiplier. Where multiple vehicle types are available – e.g. standard, motorbike, premium – the NLS function may also consume the vehicle type selected by the user for the ride and output the augmented surge multiplier

based on the vehicle type. In other embodiments, there may be multiple NLS functions, each producing an augmented surge multiplier for a different subset of rides – e.g. one NLS function for standard vehicle rides and another for premium vehicle rides. This enables coefficients to be optimized based on vehicle type, or other parameters as desired.

Step 110 involves outputting an augmented surge multiplier. The augmented surge multiplier is an automatic and intelligent approach to adjust the fares for trips in different distance buckets, with the expert knowledge of the latest market behaviours using ML techniques, to optimize for specific business objectives including GMV and ride conversions. Eventually, fares are automatically adjusted through the NLS function, which consumes the original surge and distance as inputs and gives the augmented surge multiplier as output. Where the inputs include a ride type, or other level of service, the augmented NLS multiplier may be based on the level of service.

Figure 4 illustrates a block diagram of a system 100 for determining non-linear surge pricing. The system 100 comprises at least one processor 102, memory 108 accessible to the processor 102 and a network interface 108 to facilitate communication with a plurality of driver's computing devices 150 and user's computing devices 160, to deliver augmented surge price figures thereto. Program code 106 provided in memory 104 comprises instructions executable by the processor 102 to perform at least a part of the method of the embodiments described herein. The program code 106 implements an elasticity modeller 107 for producing the passenger and driver behaviour models (PAX and DAX), an optimiser 109 for optimising the objective function and an augmented NLS calculator 111 for calculating the augmented NLS on receipt of a ride request, distance and, where appropriate, a ride type.

Notably, while individual computer systems are described in Figure 4, any such computer system may be distributed across multiple servers or multiple devices, or some functionality may be consolidated into a single server or device, without

departing from the purposive intent of the present disclosure. To illustrate, while database 120 and memory 104 are separate, and database 120 is located remotely of the system 100, the database 120 and memory 104 may be in a single unit, one may be within the other, each may be distributed, or any other combination.

Network 130 facilitates communication between the various devices and may include one or more communication networks including the internet, cell phone networks etc.

One or more database 120 are also accessible to the system 100. The database 120 comprises passenger and driver records. The records may include historical data relating to rides taken by passengers or rides provided by drivers and associated information. The historical data relating to the rides may include time, date of the ride, origin, destination of the ride, distance, vehicle type, weather and other information.

The system 100 optimises pricing for rides based on surges in demand, to achieve particular objectives, whether they are revenue based, aimed at clearing the market, intended to redistribute supply across a geographical area or other objectives.

The present methodologies extend or augment an existing dynamic pricing component – augmented NLS surge – to achieve a new objective. Specifically, NLS is able to augment the initial surge pricing component, which may have been designed for a specific objective – e.g. clearing the market – using another optimisation framework to achieve another objective – GMV maximization for instance. It is also possible for the dynamic pricing component to achieve multi-objectives and is also easily tunable for other objectives for future roadmaps. Currently, NLS can be used for GMV maximization, rides conversion maximization, or used for supply crunch surge. The augmented NLS surge models both the passengers' and drivers' behaviours in a tractable manner such that the overall product is able to achieve a good trade-off between accuracy,

performance and optimality. The augmented NLS model is customisable across time and locations (or TT), can be tuned for more aggressive or conservative settings, can achieve single or multiple goals,

It will be appreciated that many further modifications and permutations of various aspects of the described embodiments are possible. Accordingly, the described aspects are intended to embrace all such alterations, modifications, and variations that fall within the spirit and scope of the appended claims.

Throughout this specification and the claims which follow, unless the context requires otherwise, the word "comprise", and variations such as "comprises" and "comprising", will be understood to imply the inclusion of a stated integer or step or group of integers or steps but not the exclusion of any other integer or step or group of integers or steps.

The reference in this specification to any prior publication (or information derived from it), or to any matter which is known, is not, and should not be taken as an acknowledgment or admission or any form of suggestion that that prior publication (or information derived from it) or known matter forms part of the common general knowledge in the field of endeavour to which this specification relates.

Claims

1. A system for determining nonlinear surge pricing, comprising:
 - memory; and
 - a processing system comprising one or more processors, the memory storing instructions that, when executed by the processing system, cause the system to:
 - obtain historical data relating to uses of a service by one or more users, and provision of the service by one or more providers;
 - determine a user pricing elasticity model and a provider pricing elasticity model from the data relating to the uses of the service and provision of the service;
 - obtain an original nonlinear surge pricing model and service parameters;
 - optimise an objective function based on a weighted combination of a predicted number of uses of the service and a predicted gross merchandise value (predicted GMV), the original nonlinear surge pricing model, the service parameters and one or both of the user pricing elasticity model and the provider pricing elasticity model;
 - output an augmented surge multiplier for a new request for use of the service, based on the optimised objective function and a surge multiplier determined from the original surge pricing.
2. The system of claim 1, wherein the data relating to the uses of the service and provision of the service comprise service parameters for a plurality of requested uses of the service, the system determining the user pricing elasticity model and the provider pricing elasticity model by:
 - applying coefficients to the service parameters to produce modified service parameters; and
 - using linear regression on the modified service parameters,wherein a sign of coefficients is constrained to maintain causality between, for each requested use of the service, the service parameters

and usage of the service.

3. The system of claim 2, wherein the requested uses of the service comprise cancelled uses.
4. The system of claim 3, wherein the system identifies a level of service in the new request for use of the service and outputs the augmented surge multiplier based on the level of service.
5. The system of claim 1, wherein the system receives one or more limits each limit defining a minimum or maximum surge multiplier, and the objective function is optimised within the limit or limits.
6. The system of claim 5, wherein the one or more limits include a minimum ratio, and a maximum ratio, between a surge price determined from the original nonlinear surge pricing model and a surge price determined from the augmented surge multiplier.
7. The system of claim 1, wherein the system is configured to determine the weighted combination by applying a number between "0" and "1" for each of the predicted number of uses and the predicted GMV.
8. The system of claim 7, wherein the system is configured to determine the weighted combination by applying a "0" for one of the predicted number of uses and the predicted GMV, and a "1" for the other of the predicted number of uses and the predicted GMV.
9. The system of claim 1, wherein the service parameters comprise a level of service and the system optimises the objective function separately for each level of service.
10. The system of claim 9, wherein the historical data relates to a plurality of requested uses of the service, each request comprising a level of service,

and wherein system determines a separate user pricing elasticity model and provider pricing elasticity model for each level of service.

11. The system of claim 9, wherein outputting the augmented surge multiplier comprises outputting a separate augmented surge multiplier for each level of service.

12. A method for determining nonlinear surge pricing, comprising:

- obtaining historical data relating to uses of a service by one or more users, and provision of the service by one or more providers;

- determining a user pricing elasticity model and a provider pricing elasticity model from the data relating to the uses of the service and provision of the service;

- obtaining an original nonlinear surge pricing model and service parameters;

- optimising an objective function based on a weighted combination of a predicted number of uses of the service and a predicted gross merchandise value (predicted GMV), the original nonlinear surge pricing model, the service parameters and one or both of the user pricing elasticity model and the provider pricing elasticity model;

- outputting an augmented surge multiplier for a new request for use of the service, based on the optimised objective function and a surge multiplier determined from the original surge pricing.

13. The method of claim 12, wherein the data relating to the uses of the service and provision of the service comprise service parameters for a plurality of requested uses of the service, the method comprising determining the user pricing elasticity model and the provider pricing elasticity model by:

- applying coefficients to the service parameters to produce modified service parameters; and

- using linear regression on the modified service parameters, wherein a sign of coefficients is constrained to maintain causality

between, for each requested use of the service, the service parameters and usage of the service.

14. The method of claim 13, wherein the requested uses of the service comprise cancelled uses.
15. The method of claim 14, comprising identifying a level of service in the new request for use of the service and wherein outputting the augmented surge multiplier comprises outputting an augmented surge multiplier based on the level of service.
16. The method of claim 12, comprising receiving one or more limits each limit defining a minimum or maximum surge multiplier, and wherein the objective function is optimised within the limit or limits.
17. The method of claim 16, wherein the one or more limits include a minimum ratio, and a maximum ratio, between a surge price determined from the original nonlinear surge pricing model and a surge price determined from the augmented surge multiplier.
18. The method of claim 12, comprising determining the weighted combination by applying a number between "0" and "1" for each of the predicted number of uses and the predicted GMV.
19. The method of claim 18, comprising determining the weighted combination by applying a "0" for one of the predicted number of uses and the predicted GMV, and a "1" for the other of the predicted number of uses and the predicted GMV.
20. The method of claim 12, wherein the service parameters comprise a level of service and the method optimises the objective function separately for each level of service.

21. The method of claim 20, wherein the historical data relates to a plurality of requested uses of the service, each request comprising a level of service, and wherein the method comprises determining a separate user pricing elasticity model and provider pricing elasticity model for each level of service.
22. The method of claim 20, wherein the method outputs the augmented surge multiplier by outputting a separate augmented surge multiplier for each level of service.