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Modelling Noise Behaviour Taxes and Mitigating Climate Change in Sustainable Eco-Cities of Monarchy of Concordia

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ABSTRACT

The objective of the paper is to develop a model and a conceptual framework for noise behaviour monitoring and mitigating climate change by imposing global environmental taxes and externalities on "Noise Behaviour" through the monarchy of Concordia. The paper has presented the modelling of noise behaviour taxes and tariffs and climate change mitigation in the monarchy of Concordia. The Design of Experiment (DoE) for modelling "Noise Behaviour Taxes" with the statistical method of "Response Surface Methodology and Robust Parameter Design (Taguchi Technique)" has been utilized. The concepts of energy efficiency and societal well-being are presented by defining energy intensities and noise.

Keywords: environmental taxes, energy intensities, noise, sustainable eco-cities, monarchy of Concordia, climate change

1. INTRODUCTION

Noise is defined as a sensation of unwanted intensity of a wave. It is the perception of a pollutant and a type of environmental stressor. The unwanted intensity of a wave is the propagation of noise due to the transmission of energy source waves (viz. physical agents) such as sun, light, sound, heat, electricity, fluid and fire. Human Noise Behavior is checked by identifying a source and a sink of noise [1].

The econometric model is developed to estimate the noise behaviour taxes and tariffs due to global GHG emissions. Scenarios of desalination, zero-carbon-ready buildings and cities are briefly described in the context of energy efficiency and societal well-being. Some examples of green-house gas emissions are also provided for estimation and prediction of "Noise Behaviour".

1.1 Economic Criteria for Energy Efficiency

Economic systems operated by enterprises and other controlled social economic systems are driven by profits and/or budget allocations. Any new commercial activity can be justified only if it is cost effective, which in simple lay man terms must show a profit improvement or cost reduction greater than the cost of the activity. Energy efficiency has demonstrated time and again that it is a cost-effective activity. The gross domestic product (GDP) for a nation is the monetary sum of all goods and services as well as new investments for a one-year period. Economic activity is measured by GDP in a society and is often indicator of well-being of the society. A change in the ratio of a particular good or service relative to the GDP occurs only when the mix of goods and services produced by the economy changes. Energy produced for providing goods and services is neither a good nor a service produced by the economy. An average energy intensity for the overall economy can be obtained by: EI = (energy consumption rate/GDP). Available economic input-output data tables may be utilized to determine the overall energy requirements for various energy-producing or conserving scenarios. The energy required to produce a system may be obtained by knowing its investment cost using the energy value of the appropriate economic sector.

Emphasis on clean energy and transportation technologies with focus on generation of no or minimal noise is dependent on energy policy framework for controlling noise and human noise behavior, viz., identifying a source and a sink of noise i.e., a person making noise in the environment and a person affected by such noise in the environment. Sustainable Eco-Cities in the monarchy of Concordia (MoC) follow rules of zero waste in its economy. The eco-city concept involves sustainability goals in cities, with transport, energy, and buildings with smart city services [1, 2]. The monarchy

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of Concordia is proposing business models in which various international governments and people are charged taxes and fines on noise behavior and creating noise pollution in similar lines of climate change through noise scales invented by the author with energy perspective on a per capita basis. The concept of low carbon circular economy is realized for better economy, growth, and sustainable development in these eco-cities. In the monarchy of Concordia, as a globalized society, there are no income taxes on its enterprises and employees [1].

2. NOISE CHARACTERIZATION AND MEASUREMENT

A unified theory for stresses and oscillations is proposed by the author. The following standard measurement equations are derived and adopted from the standard definitions for sources of noise interference as developed by the author [3-5].

Noise of Sol: For a pack of solar energy wave, the multiplication of solar power storage and the velocity of light gives solar power intensity I. On taking logarithm of two intensities of solar power, I_1 and I_2, provides intensity difference. It is mathematically expressed as:

$$Sol = \log(I_1)(I_2)^{-1} \qquad (1)$$

Whereas logarithmic unit ratio for noise of sol is expressed as *Sol*. The oncisol (oS) is more convenient for solar power systems. The mathematical expression by the following equality gives an oncisol (oS), which is $1/11^{th}$ unit of a *Sol*:

$$oS = \pm 11\log(I_1)(I_2)^{-1} \qquad (2)$$

Noise of Therm: For a pack of heat energy wave, the multiplication of total power storage and the velocity of light gives heat power intensity I. The pack of solar energy wave and heat energy wave (for same intensity I), have same energy areas, therefore their units of noise are same as *Sol*.

Noise of Photons: For a pack of light energy beam, the multiplication of total power storage and the velocity of light gives light power intensity I. The pack of solar energy wave and light energy beam (for same intensity I), have same energy areas, therefore their units of noise are same as *Sol*.

Noise of Electrons: For a pack of electricity wave, the multiplication of total electrical storage and the velocity of light gives electrical power intensity I. The pack of solar energy wave and electricity wave (for same intensity I), have same energy areas, therefore their units of noise are same as *Sol*.

Noise of Scattering: For a pack of fluid energy wave, the multiplication of total power storage and the velocity of fluid gives fluid power intensity I. On taking logarithm of two intensities of fluid power, I_1 and I_2, provides intensity difference. It is mathematically expressed as:

$$Sip = \log(I_1)(I_2)^{-1} \qquad (3)$$

Whereas, logarithmic unit ratio for noise of scattering is *Sip*. The oncisip (oS) is more convenient for fluid power systems.

The mathematical expression by the following equality gives an oncisip (oS), which is $1/11^{th}$ unit of a *Sip*:

$$oS = \pm 11\log(I_1)(I_2)^{-1} \qquad (4)$$

For energy area determination for a fluid wave, the water with a specific gravity of 1.0, is the standard fluid considered with power of ±1 Wm^{-2} for a reference intensity I_2.

Noise of Scattering and Lightning: For a pack of fire wave, the intensity, I, of fire flash with power of light, is the multiplication of total power storage and the velocity of light. Whereas for a pack of fire wave, the intensity, I, of fire flash with power of fluid, is the multiplication of total power storage capacity and velocity of fluid.

For a noise due to fire flash, the collective effect of scattering and lightning is obtained by superimposition principle. For same intensity I, the pack of solar energy wave and a fire flash with light power have same energy areas, therefore their units of noise are same as *Sol*. The therm power may also be included in fire flash with power of light. For same intensity I, the pack of fluid energy wave and a fire flash with fluid power have same energy areas, therefore their units of noise are same as *Sip*. In determining the areas of energy for the case of fluids other than water, a multiplication factor in specific gravity has to be evaluated.

Noise of Elasticity: For a pack of sound energy wave, the product of total power storage and the velocity of sound gives sound power intensity I. On taking logarithm of two intensities of sound power, I_1 and I_2, provides intensity difference. It is mathematically expressed as:

$$Bel = \log(I_1)(I_2)^{-1} \qquad (5)$$

Whereas, logarithmic unit ratio for noise of elasticity is *Bel*. The oncibel (oB) is more convenient for sound power systems. The mathematical expression by the following equality gives an oncibel (oB), which is $1/11^{th}$ unit of a *Bel*:

$$oB = \pm 11\log(I_1)(I_2)^{-1} \qquad (6)$$

There are following elaborative points on choosing an *onci* as $1/11^{th}$ unit of noise: i) Reference value used for I_2 is -1 W m^{-2} on positive scale of noise and 1 W m^{-2} on negative scale of noise. In a power cycle, all types of wave form one positive power cycle and one negative power cycle. Positive scale of noise has 10 positive units and one negative unit. Whereas, negative scale of noise has 1 positive unit and 10 negative units; ii) Each unit of sol, sip and bel is divided into 11 parts, 1 part is $1/11^{th}$ unit of noise; iii) The base of logarithm used in noise measurement equations is 11; iv) Reference value of I_2 is -1 W m^{-2} with I_1 on positive scale of noise, should be taken with negative noise measurement expression, therefore it gives positive values of noise; v) Reference value of I_2 is 1 W m^{-2} with I_1 on negative scale of noise, should be taken with positive noise measurement expression, therefore it gives negative values of noise. vi) The ratio of the intensity of an energy source to the reference intensity is known as the intensity level of the given energy source; vii) The scale adopted for the measurement of intensity level is the common logarithmic scale. There are following reasons for adoption of logarithmic scale: a) The human senses respond to an extremely wide range of intensity beginning from sensation and perception of a physical source of energy. The utility of the logarithmic scale helps in thinning down the numerical range between these very meagre and very intense source of energy; b) the logarithmic scale simplifies the calculation of intensities by replacing multiplication by addition; c) according to Weber-Fechner law the response of any sense organ is proportional to the logarithm of the magnitude of the stimulus, this directly gives the intensity level on the logarithmic scale proportional to sensation estimates of relative intensity. The choosing of *onci* in noise units is done so as to have separate market product & system of noise scales and their units distinguished from prevailing *decibel* units (which has its limitations) in the International System of Units. More discussions on energy conversion, noise characterization theory and choice of noise scales and its units are presented in many papers by the author [3-6].

3. DESALINATION

One of the important issues connecting energy efficiency with our living economy is the energy-water-environment nexus [7]. Energy is required for obtaining potable water by different means and methods. In regions of the earth and around costal zones, where there is scarcity of water, the potable water can be obtained by treating saline sea water by way of desalination technologies. The treatment of brackish water demands significant amounts of energy depending on concentrations of salt in the seawater and is the cause of environmental pollution, effecting marine life through discharge of brine back into the sea. The process of desalination is based on energy driven almost entirely from fossil fuels. These fossil fuels are limited, and they pollute the air and add to the global climate change.

3.1 Energy Requirements

Desalination processes in the world are approximately consuming 75.2 TWh per year with their CO2 emission is expected to increase 218 Mt per year by the year 2040 [7]. Desalination process has no major technical hurdles for supplying uninterrupted fresh water. The only major challenge is that conventional desalination processes consume very large amount of energy. The energy cost of desalination process is around 0.86 kWh m^{-3} for conversion of seawater with saline content of 34,500 ppm at a temperature of 25 °C [8]. The cost for desalination has considerably reduced in recent years, and in the US, it is approximately \$0.5–1m^{-3} [8]. This amounts to equivalent energy consumption of 3 kJ kg^{-1}. The current scenario is that desalination plants consume about 5 to 26 times as much from this theoretical value depending upon the type of desalination process used. There is requirement to make desalination processes as much as energy-efficient to improve the technologies and economies of scale.

3.2 Sustainability

There is an urgent need to address sustainability issues by replacing conventional technoligies by renewable energy sources and adopting energy efficient sustainable technologies [9]. The technologies like microbial desalination cell (MDC) have demonstrated that potable water can be obtained without the use of any external electrical power [10]. The desalination can also be powered by renewable sources such as solar and wind energy [11]. The various methods of solar powered desalination include solar stills, solar membrane distillation, concentrated solar power (CSP) based desalination, solar pond distillation solar powered humidification-dehumidification desalination and solar diffusion driven desalination [12]. With range of medium to high temperature in concentrated solar power collectors, traditional thermal desalination can be made sustainable by integrating with multi-effect desalination (MED), multistage flash distillation (MFD) and vapor compression distillation (VCD) [13]. Solar membrane distillation for desalination is a feasible method to solve water and energy resources nexus [14]. The photovoltaic powered system can also be utilized in number of ways such as photovoltaic thermal-compound parabolic concentrators (PVT-CPC) [15]. They can be integrated into the single slope solar still (SS-SS) through a heat exchanger placed in the basin of the solar still. Thermal desalination can also be benefitted by technologies like pulsating heat pipe (PHP) as a fast responding, flexible and high-performance thermal conducting device [16]. The desalination can also be powered by wind energy [17]. In addition to desalination, coastal zones with narrow continental shelves can be utilized for implementing Seawater Air Conditioning (SWAC) of a renewable and low CO2 emission cooling process. The combination of SWAC and reverse osmosis (RO) desalination can also be utilized with the objective of providing desalinated cold water for integrated water supply and cooling services, termed as Deep Seawater Cooling and Desalination (DSCD) [18].The flow chart of energy processes in reverse osmosis desalinaion plant is illustrated in Figure 1. Table 1 has presented these energy processes and noise sources for a reverse osmosis desalination plant [19].

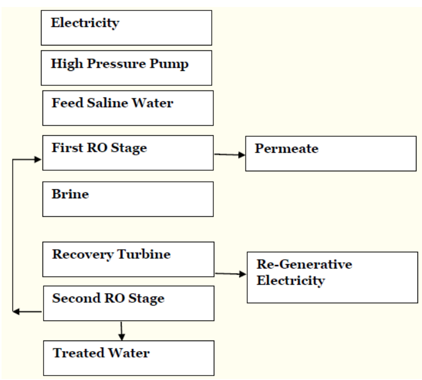

Figure 1. Flow Chart of Energy Processes in Reverse Osmosis Desalination Plant

Table 1: Energy Processes and Noise Sources in Reverse Osmosis Desalination Plant (Capacity: 150 billion litres per year) [19]

Noise Sources	Power Consumption (kW)	Noise Sources	Power Consumption (kW)
Seawater Pumps (2 units)	761	RO Flushing Pumps	209
Backwash Air Blowers	169	Chemical Service Pumps (2 units)	90
Clarified Water Return Pump	75	Permeate Pumps (2 units)	200
Backwash Pump (3 units)	60	Treated Water Transfer Pumps (2 units)	2604
Feed Booster Pumps (8 units)	900	Feed Pumps (4 units)	1103
RO Ventilation (8 units)	71	Cleaning in Place (CIP)	105

Note: The reverse osmosis desalination plant uses approx. 90 MW of electricity consumption from the grid and releases approximately 183807576 kg CO_2e per annum.

4. MONITORING AND CONTROLLING HUMAN NOISE BEHAVIOUR

The monarchy of Concordia has motto of "Controlling Human Noise Behaviour" with guiding principles of energy perspectives in a society. To monitor and control human noise behaviour, it is essential to incorporate the guiding principles of energy perspectives into a globalized society [6]. The harmonization of trade regulations and laws across countries would lead to full globalization. Such harmonization would require a global government. To overcome all such barriers and national sovereignty issues, a globalized society for maintaining peace and harmony among nations through monitoring and controlling human noise behaviour of the world came into existence by establishing sovereign political power of monarchy of Concordia. Figure 2 presents an overview of the five wings of the monarchy of Concordia [6].

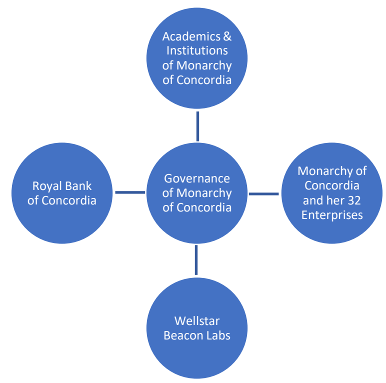

Figure 2. Five Wings of Monarchy of Concordia

4.1 Design of Experiment (DoE)

The experimental approach is important in econometrics because it offers a possible way for regression analysis to provide evidence of causality. If one group is exposed to a particular policy (like an increased environmental tax) and a control group isn't, then any meaningful difference between the behaviour of the two groups is evidence that the policy caused that difference [20]. Although a general set of guidelines and procedures for performing the design of experiments (DoE) exists, there is a requirement of action for finding and selecting the optimal design of experiments among a large range of possible designs [21]. The Design of experiments (DoE) process comprises [22, 23]: i) State the problem or area of concern; ii) State the objective of the experiment; iii) Select the characteristics and measurement systems; iv) Select the factors that may influence the selected characteristics; v) Identify control and noise factors (Taguchi-specific); vi) Select levels for the factors; vii) Select the appropriate orthogonal array; viii) Select interactions that may influence the selected characteristics or go back to step (iv); ix) Assign factors to orthogonal arrays and locate interactions; x) Conduct tests described by trials in orthogonal arrays; xi) Analyze and interpret results of the experimental trials; xii) Conduct confirmation experiment.

4.2 Literature Review

To address negative externalities, governments sometimes take measures including subsidies, direct regulation, or public abatement policies. However, some argue that tightening environmental policies would crowd out private expenditures, including investment, causing adverse economic growth. As a result, environmental taxes are levied as a policy instrument to address the externalities of climate change [24, 25]. The model for the impacts of a national carbon tax on U.S. carbon emissions from fossil-fuel combustion, along with impacts on petroleum use and generation of carbon-tax revenues has been developed [26]. The model divides carbon emissions into eight sectors: Electricity, Personal Ground Travel, Freight, Aviation, Oil Refining, Other Petroleum Products, Other Natural Gas, and Miscellany. It calculates likely reductions in U.S. carbon dioxide emissions for each sector and the U.S. as a whole on an annual basis. Emissions are expressed in CO_2 (rather than carbon) and, for the most part, in metric terms. However, carbon tax rate is inputted in dollars per British (short) tons of CO_2, not metric tons (tonnes) [26]. The model is pre-inputted for a carbon tax that begins in 2016 at $12.50 per metric ton ("tonne") of CO_2 and increments thereafter by $12.50/tonne (inflation-adjusted) per year. These inputs correspond to a bill introduced by Rep. Jim McDermott (D-WA) in May 2014 [26].

4.3 Empirical modeling and data sources

Several studies have investigated the effect of environmental taxes on economic growth and carbon emissions. However, limited studies have quantitatively identified the connection between environmental taxes and technological innovations. Karmaker et al 2021 have conducted the study to investigate the causal relations between environmental taxes and environment-related technological innovation with a holistic, robust model with a significant statistical power. Their model consists of panel cointegration analysis considering the cross-sectional dependence, applied to quantify the effects of environmental taxes on environment-related technological innovation in high and middle-income 42 countries from 1995 to 2018 [25]. The policy implications of the conducted study suggest that imposing environmental taxes can accelerate the advancement of environmental-related technologies for reducing carbon emission and sustainable development in high and middle-income nations, with possible applications in a broad range of nations, particularly as an evidence base for developing nations to shorten energy transition timelines [25]. In order to develop the econometric model, here, outline of the conceptual framework, which plays a vital role in determining the appropriate variables for use in this study has been presented. Environmental taxes have been shown to work as a useful policy tool for reducing greenhouse gas emissions [25]. A negative relationship between CO_2 and environmental tax reforms has been identified, as environmental taxes tend to tax carbon emissions as the major source of greenhouse gas emissions [25]. Different data analysis models have proposed examining the connection between environmental taxes and carbon dioxide emissions [25]. The environmental taxes have improved the quality of the environment and indicated that these taxes are effective when prioritization is granted for technological innovation in the energy and environmental sectors [25-27]. Additionally, research into the linkage between environmental technology and carbon dioxide emissions is becoming prevalent and can be split into two key types: 1) the effect of environmental technology on reducing carbon emissions; and 2) supporting cleaner sources of energy. The effect of environmental patents on carbon dioxide emissions and argued that environmental technology innovation dramatically reduces carbon emissions [25]. The environmental technology innovations are preventing environmental degradation, as the studied nations have extensively promoted R&D investment in green technology to reduce greenhouse gas emissions [25]. The situation in the European Union, the United States, and China has been analysed and claimed that expenditures on R&D in the United States and the European Union were crucial for carbon reduction while they had an adverse impact on the economy of China [25]. The GDP growth is one of the key macroeconomic indicators in the making of national policy, as the main economic target continues to be the achievement of a desired growth rate. Ecological and environmental costs, however, cannot be disregarded.

4.4 Econometric model and Preliminary Results

Based on the conceptual framework and literature review, we apply the following model to evaluate the relationship between environmental (noise behaviour) taxes and technological innovation considering the economic growth (GDP) in the form of GHG emissions and research and development (R&D) expenditure as the control variables for monitoring various types of noises. The types of Noises considered are: Solid Waste Generation Vs GDP, Wastewater Generation Vs GDP, Air Pollution Vs GDP, Traffic Intensity Vs GDP, Fossil Fuel Electricity Vs GDP, Heat Generation Vs GDP, Light Pollution Vs GDP, Sound Pollution Vs GDP and Fire Power Vs GDP. These emissions of GHGs can be used to calculate noise due to Fluid/Motion Power Intensities and/or Heat Power Intensities and/or Electrical Power Intensities and/or Sound Power Intensities. The values of "Noise Behavior" of equivalent electrical power intensities from fossil fuels of some countries are provided in Table 2. However, it will only be realistic if climate change is addressed at the local city level to have real data monitoring of "Noise Behavior". Figure 3 has presented example calculation of "Noise Behaviour Tax" based on data of the USA presented in Table 2.

Table 2: Estimation of "Noise Behaviour" from per capita CO2 equivalent emissions from fossil fuels of some countries

Country	Per capita tCO2 equivalent for the year 2016	Approx. equivalent Electrical Power Intensity (Wm^{-2}) (Based on population and area of country)	Noise (OnciSol)
Canada	15.7	0.031	-15.84
USA	17.6	0.315	-5.28
India	1.96	0.437	-3.795
China	6.4	0.46	-3.52
Germany	10.4	0.941	-0.275
UK	8.1	1.127	0.55

Note: Conversion factor is 0.23314 kg CO2 produced from each kWh

Basis of Noise Behavior Tax for USA Data
A = $ 1/capita for Carbon Emissions
B = $ 0.1/sq. m or $0.03/sq. ft
C = $ 1/capita for Noise (-ve) i.e. to be substracted from the TAX
Tax USA = USD 299.3 Billion

$A := (17.6 \times 331449281 \times 1)$ $B := 0.315 \times 9372610000000 \times 0.1$ $C := -5.28 \times 1 \times 33144928$

$A = 5.834 \times 10^{9}$ $B = 2.952 \times 10^{11}$ $C = -1.75 \times 10^{9}$

$NTAX := A + B + C$ $NTAX = 2.993 \times 10^{11}$

Tax USA = USD 299.3 Billion

$$Tax = \frac{17.6x}{capita} + \frac{(0.315y)}{sqm} - \frac{5.28z}{capita}$$

Figure 3. Noise Behaviour Tax Calculation (see Table 2)

4.5 Noise Behaviour Taxes Model

A general modelling approach is being developed so that it can model noise behaviour taxes (separately for each country) based on a derived statistical regression equation applied separately for each country. Based on the data, when complete model will be built there will be separate formula for charging noise behaviour taxes for every country in this world. At present, the example of the USA data is used for modelling and optimizing noise behaviour taxes by "Response Surface Methodology and Robust Parameter Design (Taguchi Technique)". In the actual model there will be realistic actual current data of all the countries (for which there will be charge for noise behaviour taxes based on different formulas for different countries) (derived statistical regression equations). This data is modelled and optimized for achieving minimization of noise behavior tax based on forecasting of carbon emissions of CARBON TAX model data. The data for carbon emissions can also be sourced from the published sources [28]. The annual revenue/income in the monarchy of Concordia from Noise Behaviour Taxes and Tariffs has been roughly estimated to be about USD $ 2.0-3.0 trillion (from the whole world). This modelling technique can also be applied in the IoT/M2M learning for "Noise Behaviour" monitoring of smart cities and smart buildings based on real time monitoring. Machine learning algorithms can be made to analyse data through various techniques [29]. In a recent study, there is application of response surface methodology (RSM) to the hyperparameter fine-tuning of three machine learning (ML) algorithms: artificial neural network (ANN), support vector machine (SVM), and deep belief network (DBN) is performed [30]. Several commonly used regression models in the ML including the improved linear models (the least absolute shrinkage and selection operator model and the generalized linear model), the decision trees family (decision trees, random forests and gradient boosting trees), the model of the neural nets, (the multi-layer perceptrons) and the support vector machine can be introduced through Response Surface Methodology [31].

4.6 Response Surface Methodology (RSM): Overview of the RSM Method

Suppose y = y(a, b, c, ...), where y is the outcome or result or response that is to be optimized, and there are n parameters, a, b, c, ..., which can be varied [32]. It is assumed that the optimum y is the minimum y (optimization of "noise behaviour tax"). A similar analysis can be performed for maximizing y. The goal of RSM is to efficiently hunt for the optimum values of a, b, c, ... such that y is minimized. RSM works by the method of steepest ascent, in which the parameters are varied in the direction of maximum increase of the response until the response no longer increases. The objective is to optimize (minimize) characteristic of y (noise behaviour taxes with an example of the USA data, see Table 2).

Solution Procedure for RSM

- Here, n = 3 (3 parameters), since y = y(a, b, c).
- Following the RSM procedure, a linear regression analysis is to be performed on a cluster of data points in the vicinity of the initial operating point.
- A 3-level, 3-parameter experimental design array is constructed, centered around the initial operating point. Note: A 3-level, 3-parameter Taguchi design array is used here to generate the data cluster. It requires 6 data points (runs) in the vicinity of the initial operating point. The initial operating point value is also included since that data point is also readily available. Hence Taguchi technique is utilized.
- It should be pointed out that in practice, a formal Taguchi design array may not be necessary. Instead, some random variations of each variable around the operating condition can produce an effective regression analysis. In cases where it is expensive and/or time consuming to change parameters, however, a Taguchi design array is advised in order to minimize the number of necessary runs.
- For the cases with large scatter in the data, several runs at a given operating condition should be recorded, so that the effect of random noise can be somewhat cancelled out.

5. CONCLUSION

This paper has presented the concepts of energy efficiency and societal well-being by defining energy intensities, energy conversion and noise in sustainable eco-cities of the monarchy of Concordia. Energy efficiency is an important tool to address the global climate change issue and reaching the goal of sustainable development by net zero emissions. Buildings and desalination processes are the main consumers of energy and energy efficiency should be addressed in the planning stage of sustainable eco-cities context by addressing energy efficiency along with societal well-being. Monarchy of Concordia is a globalized society with objective of maintaining peace and harmony in the world by controlling human noise behaviour. In order to develop the econometric model, here, the conceptual framework, which plays a vital role in determining the appropriate variables for use in this study is presented. Environmental taxes such as "Noise Behaviour Tax" is a useful policy tool for reducing greenhouse gas (GHG) emissions.

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Kindly visit the websites http://concordia.global/ and http://wellstar-labs.com/ for more information. This YouTube video explains the concept of Controlling Human Noise Behaviour in the Monarchy of Concordia: https://youtu.be/KwxxbYvmP1c.

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